A Semantic Situation Awareness Framework for Indoor Cyber-Physical Systems

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By

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ABSTRACT


Recently, the domain of cyber-physical systems (CPSs) has emerged as a successor to the traditional embedded systems and the wireless sensor networks. The relatively new cyber-physical domain offers tight integration of control, communication and computation components to develop advanced web based application in various heterogeneous domains such as health care, disaster management, automation and environment monitoring. The applications of indoor CPSs include remote patient monitoring, smart home, etc. with focus on situation awareness via event identification from context information. The principal challenges associated with the development of situation awareness applications include uncertainty in contextual data, incomplete domain knowledge, interoperability between interconnected systems and effective utilization of spatial information.

This dissertation addresses these challenges by providing a comprehensive situation awareness framework for event comprehension utilizing raw sensor data and spatial information. Semantic web based annotation and mapping techniques are used to provide interoperability. The framework contains contextual situation awareness and location awareness stages towards achieving effective event assessment. The contextual situation awareness stage provides fuzzy abductive reasoning based architecture to transform raw physical sensor data to low-level fuzzy abstraction. These abstractions
are used for event assessment with associated degree of certainty. The location awareness stage includes methodologies to hierarchically map indoor objects and define the object-event relationship in ontology, which is further exploited for event discrimination. This dissertation also presents a fusion based indoor positioning algorithm to provide accurate spatial information to assist location awareness. The algorithm uses extensive training of received signal strength (RSS) and time difference of arrival (TDoA) signals to estimate distance and position. The comprehensive framework is evaluated through an implementation of simulated indoor fire in a controlled environment.
# Table of Contents

1 Introduction .......................................................................................................................... 1

1.1 Motivation ......................................................................................................................... 2

1.2 Justification ....................................................................................................................... 7

1.3 Dissertation contributions ............................................................................................... 11

1.4 Assumptions ...................................................................................................................... 13

1.5 Organization ..................................................................................................................... 16

2 Situation Awareness in Cyber-Physical Systems ................................................................. 19

2.1 Cyber-Physical system (CPS) ............................................................................................ 20

  2.1.1 Introduction .................................................................................................................. 20

  2.1.2 Features ....................................................................................................................... 23

  2.1.3 Examples ..................................................................................................................... 25

  2.1.4 Challenges ................................................................................................................... 27

2.2 CPS architecture ............................................................................................................... 30

  2.2.1 Traditional architecture of embedded systems ......................................................... 30

  2.2.2 System level CPS architecture ................................................................................. 31

  2.2.3 CPS versus Internet of Things (IoT) ......................................................................... 32

2.3 Situation awareness (SA) .................................................................................................. 35

  2.3.1 Introduction ................................................................................................................ 35

  2.3.2 Challenges with traditional SA approaches ............................................................... 36

2.4 Defining situation awareness in indoor CPSs ................................................................. 38

2.5 Contexts and context awareness ..................................................................................... 39

  2.5.1 Defining context ........................................................................................................ 39

  2.5.2 Defining context awareness ...................................................................................... 39
<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.5.3 Context abstraction</td>
<td>40</td>
</tr>
<tr>
<td>2.5.4 Contextual situation awareness</td>
<td>42</td>
</tr>
<tr>
<td>2.6 Location Awareness: Complementing the context awareness</td>
<td>44</td>
</tr>
<tr>
<td>2.7 Summary</td>
<td>46</td>
</tr>
<tr>
<td>3.1 Domain knowledge and semantic concepts</td>
<td>50</td>
</tr>
<tr>
<td>3.2 Deductive versus Abductive reasoning</td>
<td>52</td>
</tr>
<tr>
<td>3.3 Abductive reasoning with crisp abstraction</td>
<td>54</td>
</tr>
<tr>
<td>3.3.1 Observation process</td>
<td>55</td>
</tr>
<tr>
<td>3.3.2 Perception process</td>
<td>56</td>
</tr>
<tr>
<td>3.4 Making a case for fuzzy context abstractions</td>
<td>57</td>
</tr>
<tr>
<td>3.5 Fuzzy abductive reasoning with semantic context abstractions</td>
<td>58</td>
</tr>
<tr>
<td>3.5.1 Observation process and fuzzy semantic abstractions</td>
<td>59</td>
</tr>
<tr>
<td>3.5.2 Perception process with fuzzy abstractions</td>
<td>61</td>
</tr>
<tr>
<td>3.6 Semantic sensor web integration</td>
<td>63</td>
</tr>
<tr>
<td>3.7 Evaluation</td>
<td>67</td>
</tr>
<tr>
<td>3.8 Discussion</td>
<td>74</td>
</tr>
<tr>
<td>4 An Algorithm for Accurate Indoor Localization</td>
<td>75</td>
</tr>
<tr>
<td>4.1 Making a case for accurate indoor localization</td>
<td>76</td>
</tr>
<tr>
<td>4.2 Related work in indoor location awareness</td>
<td>79</td>
</tr>
<tr>
<td>4.2.1 Early indoor localization research</td>
<td>79</td>
</tr>
<tr>
<td>4.2.2 TDoA based indoor localization research</td>
<td>82</td>
</tr>
<tr>
<td>4.2.3 Why wireless sensor network?</td>
<td>84</td>
</tr>
<tr>
<td>4.3 The Cricket motes</td>
<td>86</td>
</tr>
<tr>
<td>4.3.1 Introduction</td>
<td>86</td>
</tr>
</tbody>
</table>
4.3.2 Cricket motes - hardware architecture.......................................................... 86
4.3.3 Cricket motes - software architecture.......................................................... 88
4.4 Traditional TDoA approach in CILS.................................................................. 91
  4.4.1 Distance estimation...................................................................................... 91
  4.4.2 Position estimation..................................................................................... 93
  4.2.3 Need for an improved localization system.................................................. 96
4.5 Proposed fusion based algorithm..................................................................... 97
  4.5.1 RSSI data training phase............................................................................. 97
  4.5.2 Distance estimation from fusion of RSSI and TDoA data...............................102
  4.5.3 Position estimation....................................................................................105
4.6 Simulation results of proposed algorithm.........................................................106
  4.6.1 Simulation environment..............................................................................106
  4.6.2 Simulation results......................................................................................107
4.7 Discussion........................................................................................................109
5 Optimization of Entity Identification Results using Spatial Information..........110
  5.1 Introduction.....................................................................................................111
  5.2 Indoor location ontology................................................................................114
    5.2.1 Object classes..........................................................................................115
    5.2.2 Spatial association object properties.......................................................117
    5.2.3 Effective coverage space and datatype properties....................................119
    5.2.4 Semantic object identification..................................................................122
  5.3 Location based situation assessment...............................................................124
    5.3.1 Object properties for relationship between individuals of PointOfInterest
and Entity............................................................................................................124
    5.3.2 Location based entity discrimination.......................................................126
7.2.2 Efficient coverage space for the indoor objects........................................168
7.2.3 Accurate indoor localization via smartphones ........................................169
References ...........................................................................................................170
List of Figures

Figure 1.1: An indoor environment with multiple events..................................................2
Figure 1.2: Focus scenario with fire as the primary event ..............................................4
Figure 1.3: Interoperability in the cyber-physical domain...............................................5
Figure 2.1: Functional components of a CPS[21].............................................................21
Figure 2.2: Evolution of Cyber-Physical Systems..........................................................22
Figure 2.3: Examples of cyber-physical systems..............................................................27
Figure 2.4: Architecture of traditional embedded systems..............................................30
Figure 2.5: Cyber-physical system architecture..............................................................31
Figure 2.6: Traditional situation awareness model.........................................................35
Figure 2.7: Context awareness model.............................................................................40
Figure 2.8: Semantic context abstractions.......................................................................42
Figure 2.9: Situation comprehension using context and location awareness...............45
Figure 3.1: A graphical representation of domain knowledge base containing
concept relationships......................................................................................................50
Figure 3.2: Observation and perception processes............................................................54
Figure 3.3: Graphical representation of reasoning rules with crisp abstractions..............54
Figure 3.4: Fuzzy abstractions and membership function \( \mu \) ........................................58
Figure 3.5: An observation ‘a’ in fuzzy range of qualities x1 and x2...............................59
Figure 3.6: Graphical representation of rules with fuzzy context abstractions..........61
Figure 3.7: An event extraction framework from contextual data aided by ontologies.
........................................................................................................................................64
Figure 3.8: Subset of Semantic Sensor Network (SSN) ontology in prospect to the framework .......................................................... 65

Figure 3.9: Ontology alignment between SSN and IntellegO ................................................. 66

Figure 3.10: The experimental setup containing two fire events and path of the mobile platform in the indoor environment ......................................................... 67

Figure 3.11: Raw sensor data from temperature and carbon dioxide sensors on the mobile robot ............................................................................................................ 72

Figure 3.12: Comparison of extracted fire entity from crisp abductive reasoning with the actual fire entity in the experiment ......................................................... 72

Figure 3.13: Comparison of extracted fire entity from fuzzy abductive reasoning with the actual fire entity in the experiment ......................................................... 73

Figure 3.14: Crisp and fuzzy abductive reasoning results for the indoor fire experiment .................................................................................................................. 73

Figure 4.1: GPS accuracy compared with size of outdoor structures ................................... 78

Figure 4.2: Comparison of indoor object on 5 meter scale ................................................ 78

Figure 4.3: Hardware architecture of Cricket motes[100] ................................................... 87

Figure 4.4: Software architecture of Cricket motes ................................................................ 89

Figure 4.5: TDoA assisted distance estimation ..................................................................... 92

Figure 4.6: Trilateration based localization ........................................................................ 94

Figure 4.7: Classical setup of an experimental indoor positioning system ....................... 95

Figure 4.8: Distance estimation error with respect to angle of ultrasonic transmitter and receiver for different distances[100]. ......................................................... 96

Figure 4.9: RSSI and TDoA updates from beacon $B_1$ ..................................................... 98
Figure 4.10: RSSI and TDoA updates from beacon B₂......................................................... 99
Figure 4.11: RSSI and TDoA updates from beacon B₄.........................................................100
Figure 4.12: RSSI and TDoA updates from beacon B₁ for the second cycle.........................101
Figure 4.13: RSSI and TDoA updates from beacon B₃ complete training table.................101
Figure 4.14: Position results for a single instance of localization in 3D space...............107
Figure 4.15: RMS error in position estimation for 25 Monte Carlo simulations..............108
Figure 5.1: System framework for location based situation assessment..........................113
Figure 5.2: Generic indoor scenario of point of interests..................................................114
Figure 5.3: Class hierarchies for indoor components and POIs........................................116
Figure 5.4: Relationship among POI individuals and structural individuals.....................118
Figure 5.5: Data properties of an indoor POI.................................................................121
Figure 5.6: Relationship between POIs and entities for different objects in the DrawingRoom-1.................................................................................................................125
Figure 5.7: Raw spatial coordinates of the indoor objects in the experimental setup. .................................................................................................................................................129
Figure 5.8: Comparison of the actual fire situation at Chair-1 and the estimated fire situation at 0.75, 0.5 and 0.25 certainty number.........................................................135
Figure 5.9: Evaluation of location aided fuzzy entity identification..................................135
Figure 6.1: System level framework..................................................................................138
Figure 6.2: Semantic modeling framework.......................................................................142
Figure 6.3: Simulated indoor fire scenario.........................................................................144
Figure 6.4: Raw physical sensor information from context source..................................145
Figure 6.5: Raw spatial data from the indoor positioning system.....................................146
Figure 6.6: Identified entities using fuzzy abductive reasoning.................................147

Figure 6.7: Translation of raw spatial information to semantic POI identifiers. ......147

Figure 6.8: Location based entity discrimination. ..........................................................148

Figure 6.9: An indoor patient monitoring scenario..........................................................152

Figure 6.10: Graph of entity detection rules for the subset of indoor patient monitoring system. ..........................................................................................................................153

Figure 6.11: Indoor objects to entity relationship for indoor patient monitoring system. .................................................................................................................................154

Figure 6.12: Extended graph to represent indoor fire scenario........................................158

Figure 6.13: Implemented rules by Patni et al. for weathercasting...............................160

Figure 6.14: Improved rules for fuzzy semantic abstractions.........................................162
List of Tables

Table 2.1: Features of a CPS. ................................................................. 23
Table 2.2: Challenges associated with the cyber-physical domain. ....................... 28
Table 3.1: Experimental results from crisp abductive reasoning. .......................... 70
Table 3.2: Experimental results from fuzzy abductive reasoning. .......................... 70
Table 3.3: Evaluation of crisp and fuzzy abductive reasoning approaches for
detecting indoor fire entity............................................................................ 71
Table 5.1: Indoor object properties and their descriptions................................. 117
Table 5.2: Datatype properties and their descriptions regarding effective coverage
area........................................................................................................ 120
Table 5.3: Object properties for relationship between POI and entities................. 125
Table 5.4: Evaluation of crisp and fuzzy abductive reasoning approaches for
detecting actual indoor fire situation.......................................................... 134
Table 6.1: Context data for observation (a)...................................................... 155
Table 6.2: Context data for observation (b). .................................................... 156
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Dedicated to
My parents and wife
1 Introduction

The domain of Cyber-Physical Systems (CPS) has emerged as successor of the traditional real-time embedded systems. The concept of CPS proposes tight integration of physical objects and web based technologies with each other using communication techniques. Typical CPSs are complex systems and include a large amount of heterogeneous physical objects communicating with each other. The traditional situation awareness and event identification approaches fail due to the presence of a huge amount of complex context information and associated uncertainties towards explaining a situation. The problem of situation awareness provide greater challenges when ported to an indoor environment due accuracy required in the spatial information. The research defines and solves three key challenges associate with the indoor situation awareness in Cyber-Physical Systems: (1) Uncertainty in context information towards identifying an event (2) Accurate indoor localization and (3) Spatial information for event discrimination. The issues of complex reasoning and interoperability are solved by implementing semantic web technologies on sensor information.
1.1 Motivation

The situation awareness problem deals with projecting the outcome from comprehended events using perception derived from context information. In CPSs, physical level embedded systems or sensor network provides this context information. Various outdoor CPS challenges such as smart grid, traffic control and indoor CPS challenges such as patient monitoring, smart home, emergency response requires knowledge discovery in forms of events or features. This dissertation specifically focuses on indoor situation awareness challenges. The motivation scenarios for the research are explained in detail by following examples.

![Figure 1.1: An indoor environment with multiple events.](image)

Recent developments in sensor and computation technologies have enabled consumer level availability of inexpensive environment monitoring sensors. With further advances and increasing acceptability, it is assumed that buildings of the future will be equipped with sensors capable of accurately measuring physical context information. Now, Figure 1.1 shows an indoor structure where various events such as fire, excessive heat, abnormal health condition are taking place. These events are
responsible for generating physical level context information such as high temperature near fireplace, large amount of Carbon Dioxide in the environment, high heart rate from a person, etc.

In the scenario displayed above, it is assumed that the indoor structure is equipped with environment motoring sensors capable of detecting temperature, Carbon Dioxide, humidity, etc. People in the building are equipped with heart rate monitoring sensor while the building itself is equipped with an indoor localization system to provide spatial information. In this cyber-physical system establishment, utilized sensors only provide environmental context data in real-time continuous form while the goal of a situation awareness system is to accurately comprehend the events from this context data. The primary motivation is to create a framework for accurately comprehension of the situation by exploiting sensory context and spatial information. The framework should also provide a solution to deal with complex model of cyber-physical system and uncertainties associated with the context information. For the explanatory purposes, this scenario can be further reduced by focusing on comprehending subset of events such as fire and presence of a room heater.
Figure 1.2 shows subsection of the scenario explained in Figure 1.1. Two separate events of fire are taking place in an indoor environment with the presence of additional event such as a room heater, which provide similar context information in terms of temperature, compare to a fire. In contrast to the fire, taking place at the fireplace, the fire occurring at the other corner is the primary event to be identified. Both these fires are responsible for environmental context information in the room such as high temperature, high Carbon Dioxide, low humidity, etc. which is being observed a mobile robot equipped with sensors. The mobile robot also observes high temperature near the room heater, but the amount of Carbon Dioxide is different compare to the locations near fires. A range based reasoning mechanism can be used for temperature and Carbon Dioxide readings to extract the fire events and differentiate them from the room heater. Although this traditional approach provides a mechanism to identify fire, the accuracy of this approach suffers in the presence of other sources generating similar
context information. In our scenario, the heater also provides high temperature context and presence of people in the room can produce higher amount Carbon Dioxide observations compare to a normal room. Thus, in this case, the event of fire cannot be explained by ordinary rule based approaches. The fire at the fireplace can be differentiated from the actual fire by exploiting background knowledge containing the spatial description of the fireplace. Porting this sub scenario back to the original environment in Figure 1.1, a mechanism is required to provide interoperability in between embedded systems observing environmental factors and the body area sensor network monitoring human heart condition.

Figure 1.3: Interoperability in the cyber-physical domain.

A complex cyber-physical system may contain multiple indoor environments designed for monitoring different events. Figure 1.3 illustrates a scenario where multiple indoor environments are equipped with heterogeneous sensors, connected to
the Internet. A fire department wants to utilize the information from the cyber-physical systems for emergency response while a health care institute wants to monitor heart condition of patients from their home. The focus events are different for the fire personnel and the doctor, but they have access to the same information from one environment while the information originating from other environment may have data in a different format. This scenario makes a strong case for interoperability requirements between cyber-physical systems.

There are multiple other challenges associated with the domain of indoor situation awareness in a cyber-physical system, which can be explained from the above scenario. The dissertation focuses on a subset of challenges identified as the major hurdle in development of the future situation awareness applications as explained via previous scenario. In summary, inspired from the explained scenarios, primary goals of the dissertation are summarized as following: (1) Provide reasoning framework to identify events from the sensor observation which handles uncertainty associated with the context information for explanation of an event. (2) Develop a methodology to discriminate between events using spatial information. (3) Provide interoperability between observations obtained from heterogeneous sensors to achieve situation awareness.
1.2 Justification

In the scenario from the previous section, due to the human cognitive abilities, a person can easily identify these events from his body sensors such as nose, eyes, skin and his ability to reason over this sensory information. The key question is how a situation awareness system in a cyber-physical system can use the sensor information observed from physical sensor to accurately identify an event. For the machine to percept the context information and reason over that data, sophisticated reasoning algorithms are required with accurate context, spatial information. Also, in machine perception, one can always question about the robustness of the sensor information and mutual dependence of these context sources.

In the past, various researchers have explored the domain of situation awareness in embedded system and wireless sensor networks. The situation awareness solutions proposed by these researchers were localized to smaller coverage area of the installed embedded systems[1], [2]. Traditional embedded system based situation awareness application used rule based and decision tree based reasoning mechanism. Due to the small amount of sensors participating in the event detection process, these approaches are applicable up to a scale. The successor technology of the traditional embedded systems, i.e. the cyber-physical systems expect a large number connected sensor from multiple embedded systems. Thus, the cyber-physical systems have a complex architecture and traditional generic rule based algorithms are not scalable for the knowledge discovery. In recent times, the domains of indoor situation awareness and event identification were also explored by implementing similar techniques[3]. In
summary, the traditional embedded system based situation awareness application lacks scalability for complex systems, interoperability between multiple embedded systems and mechanism to handle uncertainty associated with the context information.

Contemporary event detection approaches for sensor based perception uses deductive process that mean it utilizes context information from the sensors to identify events. Henson et al. introduced abductive reasoning based approach to extracts event for machine perception [4],[5]. Basically, the abductive process argues that the event explains the responsible context and it is not suitable to conclude the event from the context information. For example, a fire is responsible for high temperature context and the concept of high temperature is dependent upon the event of fire as for the event of normal room condition, the high temperature concept can have different values. A practical implementation of abductive reasoning based event detection for real-time sensor data was conducted as the primary part of our research[6]. This approach uses semantic web technologies to provide interoperability between different systems and also provides scalability for complex systems. The primary challenge, identified during this implementation, was related to the uncertainty associated with the sensor information due to the presence of other similar context source in the premises. In summary, the abductive framework, utilized in this implementation, provide interoperability and scalability but not capable of providing a mechanism to handle uncertainty.

The concept of uncertainty is associated with the sensor context perception and not with the event to be identified. Fuzzy logic based technologies are widely used in
embedded system to deal with uncertainty associated with real-time sensor data. The concept of fuzzy logic has been used by multiple researches to handle uncertainty in location information for a multi-robot situation awareness system and in environment monitoring sensor perceptions for smart home application[7],[8]. In recent times, various researches provided successful implementation of fuzzy logic based approach for event detection in the wireless sensor network and cyber-physical systems[9],[10]. These approaches used basic rule based approaches to extract events from the raw sensor data. Although these approaches provide methods to handle uncertainty associated with sensor perception, they neither scale to provide interoperability nor implement abductive reasoning for event identification. Anagnostopoulos et al. introduced similarity based reasoning approach for situation awareness on user-generated data such as emails and web pages. Their approach provides semantic methods to model uncertainty but not designed to handle sensor based context information nor implement preferred abductive reasoning for the cyber-physical systems[11].

Beside use of the sensor generated context information, the spatial information of the sensor or the sensor mounted platforms can assist the process of event identification. Traditional event identification researches for indoor situation awareness application have limited scope for bigger picture of cyber-physical systems[12],[13]. The primary limitation is the absence of a sophisticated mechanism to provide interoperability between indoor localization systems, in terms of semantic annotation of indoor objects. In the domain of semantic web, Wang et al. provided methods for
modelling the indoor objects in form of ontologies [14]. This approach does not deal with modeling of relations between extracted events and the indoor objects. The semantic annotation of indoor objects needs location information of the context source, the sensors or the embedded platform. Due to small factor of the indoor objects, an accurate indoor localization algorithm is required which can use existing cyber-physical system structure to provide spatial information. Requirements for an accurate localization algorithm and developments in that direction are discussed in chapter 5.

The objective of this dissertation is to solve major challenges towards development of an indoor situation awareness framework for the cyber-physical system, identified as follow: (1) handling uncertainty associated with context information and incomplete domain knowledge for event identification (2) Development of an accurate indoor localization algorithm (3) Utilization of obtained spatial information for event discrimination and (4) Providing interoperability between various components of cyber-physical systems.
1.3 Dissertation contributions

The development of solutions requires a collaborative approach to achieve the specified objectives, which utilizes multiple heterogeneous domains such as semantic web, fuzzy logic, abductive reasoning and indoor localization. The semantic web and the abductive reasoning based event identification approach provide interoperability between the complex CPSs but fail to handle uncertainty in context information and incompleteness in the domain knowledge. Extension of this approach to integrate fuzzy logic provides a mechanism to handle uncertainty for the machine perception. Although the location provides useful information regarding the ongoing events, a methodology is required to integrate the spatial information in the event reasoning mechanism to achieve efficient situation awareness results. The objectives of uncertainty modeling using fuzzy logic, location-based reasoning and estimation of accurate indoor location were solved using new theoretical developments and extension of existing approaches. The detailed research contributions towards solving these challenges are briefly described as follow.

1. The dissertation proposes a novel framework for indoor situation awareness for cyber-physical systems. It provides development and deployment strategy for efficient event identification as applied to a prototype cyber-physical system scenario. Due to use of semantic web based methodologies to provide interoperability, this framework can be used as a model to create complex situation awareness application for other domains.
2. Uncertainty modeling and event identification:
   a. The dissertation introduces fuzzy logic based context abstraction to physical sensor information.
   b. This dissertation research provides novel methods to integrate fuzzy abstraction and inference rules with existing abductive reasoning framework for event identification.
   c. The semantic web based annotation standards and reasoning mechanism provides interoperability between cyber-physical systems.

3. Accurate indoor localization:
   a. The dissertation presents a novel algorithm to provide accurate location information using fusion of RF signal and ultrasonic signals.
   b. This algorithm implements a method for utilization of known locations of sensor nodes and extensive training to identify the environmental loss factor for radio signals. The algorithm then exploits this environmental loss factor to provide distance estimation results in the absence of ultrasonic signals.

4. Optimized event identification and situation awareness based on spatial information:
   a. The dissertation introduces a unique method for modeling indoor point of interest in ontology from acquired indoor positioning results.
   b. This research also introduces methods for semantic web based approach for event discrimination from spatial information modeled in the ontology.
1.4 Assumptions

The domain of cyber-physical systems is extremely broad. It covers multiple heterogeneous domains covering sensors interacting with the physical environment, communication techniques and computation interface for integration and reasoning. Each of these domains also contains various subdomains. Although the current research attempts to cover considerable challenges associated with the indoor situation awareness problem in the cyber-physical domain, various components orthogonal to the proposed framework are not in scope of this research. This section explicitly mentions those components not researched and omitted from the dissertation research. Towards creating this framework, some assumption related to characteristics of context information and regarding the availability of resources were made. The assumptions and out of scope components are discussed in a hierarchical manner as following.

a. Framework level:

1. Although the dissertation provides an example scenario of a cyber-physical system, development of domain specific complex applications is out side the scope for this research.

2. The dissertation does not focus on creating an actual cyber-physical system; rather it provides an application framework on existing systems.
b. Physical level:

1. Improving the quality of sensor data or providing robustness in the sensor operation is outside the scope of this dissertation.

2. The dissertation focuses on the uncertainty associated with context abstraction, but the quality of actual sensor reading is assumed to be robust.

3. Like any cyber-physical system, it is also assumed that the physical context information collected from the sensor are continuous and in real-time.

c. Cyber level:

1. The dissertation provides strategies to utilize the concept of context abstraction for event identification, but development of methods for obtaining ranges for these abstracts is outside the scope of this dissertation report.

2. It is assumed that the domain knowledge regarding the fuzzy ranges for abstractions, utilized in the example scenario, is obtained from a domain expert.

3. The relation between the events and context information in the example scenario is obtained from a domain expert. These relations are also limited to the simulation of the example scenario. Actual number of events and related context sources are application specific and may vary according to the event priority.
d. Cyber-Physical interface level:

1. Explanation or development of networking methods for communication between the sensing platform and application platform is out of scope for this research.

2. The dissertation utilized Zigbee, WiFi and Ethernet protocol for communication but their explanation is omitted from this report.

3. It is assumed that these communication protocols provide robust and reliable mean of transport between physical and cyber systems.
1.5 Organization

This section outlines the dissertation report with contextual summary of the chapters. Chapter 2 introduces the domain of situation awareness in the cyber-physical system. Chapter 3 through Chapter 5 explains the core theoretical and application development as a solution to the challenges associated with the research domain. Chapter 6 presents the proposed framework while Chapter 7 concludes the research with some application cases and future work. The brief summaries of the remaining chapters are as following:

Chapter 2 introduces the domain of cyber-physical systems with associated features, challenges and architectures. The chapter also introduces the concept of situation awareness and challenges associated with traditional situation awareness approaches. Later, the chapter defines the concept of indoor situation awareness in the cyber-physical systems domain. The chapter also introduces the concept of context awareness and location awareness and their association and signification for the situation awareness applications. In brief, Chapter 2 describes and justifies the problem to be solved in the research.

Chapter 3 introduces the concept of sensor context abstraction and their significance in entity identification. The chapter explains the uncertainty associated with the different level of cyber-physical system with the requirement of handling the uncertainty and applicable approaches. The chapter then introduces the concept of fuzzy context abstraction for physical level context information. The chapter also explains theories and methodologies to implement fuzzy inference rules and reasoning
for entity identification in the cyber-physical systems. Chapter 3 briefly explains the foundation of the semantic web and justification of semantic web integration with the proposed system. It also introduces the semantic sensor network ontology and semantic annotation techniques for cyber-physical system context information. After describing methods for modeling fuzzy context and event abstraction sets in ontologies, the chapter explains methods for using semantic reasoning on fuzzy abstraction sets.

Chapter 4 focuses on the development of an accurate indoor localization algorithm to assist proposed situation awareness framework. In the beginning of this chapter, related work in the field of the indoor localization is discussed. Later, the chapter justifies the selection of wireless sensor networks based indoor localization platform with a brief description of its components. The chapter then explains traditional wireless sensor network based localization approach, limitation of that approach and necessity of a robust algorithm. A fusion based algorithm, which uses extensive training of radio signal and uses time difference of arrival approach as reference is proposed later in the chapter. In the end, the simulation evaluation of the proposed localization algorithm is presented in comparison of traditional localization approaches.

Chapter 5 focuses on explaining location awareness and use of location awareness to aid context awareness results. The chapter describes methodology to model indoor point of interests in ontology with their location information and their association with the context sources and events to be monitored. It also provides few
applicable cases of proposed approach of integration of spatial information for achieving situation awareness.

Chapter 6 explains the generalized situation awareness framework for cyber-physical systems by systematically organizing components in previous chapters. The chapter describes each component in the framework and interoperability issues in between components. Later, the chapter illustrates few scenarios of situation awareness in cyber-physical systems at entity identification level. The chapter also describes methodologies to implement the proposed framework into a functional system for above scenarios.

Chapter 7 concludes the report by briefly answering the three questions: Why does this research required? What is the problem being solved? How is the solution of the problem achieved? The chapter also describes the future work required for solving other challenges with cyber-physical systems.
2 Situation Awareness in Cyber-Physical Systems

This chapter defines the problem of situation awareness in the domain of indoor cyber-physical system and describes effects of the context and location awareness on the situation awareness results. The chapter starts with the introduction of the cyber-physical systems features and challenges in section 2.1. Section 2.2 explains system level architecture of generic cyber-physical system and its comparison with Internet of Things (IoT). Section 2.3 describes the concept of traditional situation awareness and challenges associated with it. Section 2.4 focuses on the situation awareness problem for the indoor cyber-physical systems. Section 2.5 defines context awareness and context abstraction with their significance on situation awareness. Section 2.6 briefly explains how location awareness complements the context awareness and improves efficiency of the situation awareness and the summary of this chapter discussed in Section 2.7
2.1 Cyber-Physical system (CPS)

2.1.1 Introduction

In 1970, the Apollo command module used a digital computer, Apollo Guidance Computer (AGC), with 2.048 MHz processor that consumed 55W power[15]. The AGC contained a large football sized Inertial Measurement Unit (IMU) and other navigation sensors, which represented most advanced embedded system of that age[16]. After 50 years, latest smart phone used by the average citizen has 1 GHz processor and can compute a lot more data with faster speed than the AGC. Similarly, advancement in sensor manufacturing technologies has made it possible to manufacture low cost, millimeter sized IMU with more accuracy than the one used on the Apollo Command Module. In the past decade, the Internet has become the platform for interaction between people and to obtain knowledge from around the world. Also, the revolution in the communication industry has enabled access to high bandwidth Internet communication. The evolution in computation, sensor and communication industry has opened up horizon for development of a new domain to fill the gap between cyber and physical world. The traditional embedded system is no more limited to a standalone system like AGC and can easily interact with the cyber world. These type of systems can be described by a new term “Cyber-Physical Systems”, first coined by Helen Gill in 2006 at the National Science Foundation in the United States. The Cyber-Physical Systems (CPSs) refers to advance system featuring tightly integrated computation and physical capabilities[17].
The CPSs augment and expand human ability to interact and monitor physical entities by cohesive control, communication and computation core as shown in Figure 2.1[18]. These three ‘C’s, Control, Communication and Computation, are defining functional components of a full fledge Cyber-Physical system. In other terms, CPS is a multidisciplinary system which leverages breakthrough developments in system & control engineering and computer science to build large real-time computer-controlled intelligent systems[19]. The Cyber-Physical technology focuses on integrating research from various domains such as communication, networking, machine-human interactions, control theory, machine learning, embedded system, sensor fusion, semantic web, etc. to enhance human experience[20].

*Figure 2.1: Functional components of a CPS[21].*

The CPS is an evolved version of traditional embedded systems and ubiquitous computing, inheriting some characteristic of its parent technologies. Though CPS
consists of components similar to the embedded systems, they can be easily distinguished from the traditional embedded system by its extended computational and networking capabilities. As defined by Marwedel[22], the embedded systems are information processing systems embedded into composing products. The embedded system focuses on the computation features of the system and not on the link between the computation and the physical elements[18]. In contrast, the CPSs are designed to behave as intelligent networks of physical systems instead of being a standalone system. In CPSs, every component is networked at each level, and computation is deeply embedded in every physical component. Figure 2.2 shows the evolution of CPS from traditional standalone embedded system to locally networked embedded system to the current state of cyber-physical system with practical examples. Section 2.1.2 explains the defining features of a CPS system, proposed by various researches.

![Figure 2.2: Evolution of Cyber-Physical Systems.](image-url)
2.1.2 Features

Table 2.1: Features of a CPS.

<table>
<thead>
<tr>
<th>Defining Features</th>
<th>Operational Features</th>
</tr>
</thead>
<tbody>
<tr>
<td>Components are tightly coupled [17], [20]</td>
<td>Real-time operation [23]</td>
</tr>
<tr>
<td>Cyber capability at physical level [24], [25]</td>
<td>Provide interoperability between systems [23], [26]</td>
</tr>
<tr>
<td>Complex system at temporal and spatial scale [24], [25]</td>
<td>Translate raw data into knowledge [27]</td>
</tr>
<tr>
<td>Networked components at each level [24], [25]</td>
<td>Certified and secure system [24], [25]</td>
</tr>
<tr>
<td></td>
<td>Support autonomous operations [24], [25]</td>
</tr>
</tbody>
</table>

The research in CPS is in preliminary phases and does not have pre-defined industry standards or specifications, describing an exact cyber-physical system. Table 2.1 classifies requirements for CPS in categories of defining and operational features. The defining features are those requirements, which differentiate a CPS from traditional embedded or real-time system and desktop computers. The operational features are not mandatory requirements but can further assist a CPS in providing efficient cyber physical connectivity. The operation features are inherited to CPS from the traditional embedded system, sensor networks and computation applications. The features in Table 2.1 are briefly described below [23]- [27],
•  **Components are tightly coupled:** As described earlier, the principal functional components of a CPS should have closely integrated operations.

•  **Cyber capabilities at each physical level:** All components interacting with the physical environment should have computational capabilities.

•  **Complex system at temporal and spatial scale:** The system should display complex integration of components at spatial and temporal levels.

•  **Networked components at each level:** Each physical component should have networked connectivity to communicate with other component or the Internet.

•  **Real-time operation:** As the physical level components interact with real world environment, the system should have capabilities of providing real-time operation.

•  **Provide interoperability between systems:** Due to heterogeneity of physical components, interoperability is a must feature of a CPS, which can also provide connectivity between different CPSs.

•  **Translate raw data into knowledge:** To support future applications aggregating data from a large number of physical components, the system should provide a framework to autonomously translate this data in the form of knowledge, features or events.
• **Support autonomous operations:** The system should be semi or complete operator independent for decision making tasks.

• **Certified and secure system:** In the situation involving health and privacy issues, the operation should be secured and certified by an authority. This feature is application and domain specific. For example, health care application may require FDA approval.

2.1.3 Examples

In recent years, the concept of CPS has been applied in developing multiple multidisciplinary applications such as critical infrastructure, automation, health care, traffic control, disaster management, etc. In critical infrastructure domain, the CPSs are being implemented for smart energy grid[25] and water flow management. Automation and control application include smart home[28], traffic automation, plant automation, etc. The CPSs are also being used for control of large infrastructure such as air traffic control, city traffic & congestion management[26], [29], [30] and asset monitoring systems[18]. In health care domain, CPSs are being quickly adopted for remote patient monitoring application[31] and first responder systems[32]. Surveillance and tracking applications in military domain using unmanned air vehicle can also be classified as a CPS application[33]. Figure 2.3 shows few of these application domains for the cyber-physical systems.

These CPS applications can be categorized using multiple factors such as spatial coverage, scale and size, distributed or centralized and operation type i.e. continuous or event based. In this dissertation, the major factor for classification between CPSs is
identified as the spatial coverage of the CPS implementation. In terms of location based parameters, the CPSs can be classified as Indoor CPSs, outdoor CPSs or Hybrid CPS. Smart energy grid, water flow management, air traffic control, etc. are the example of outdoor CPSs, whereas home automation, remote patient monitoring, emergency response system, plant automation, etc. are examples of indoor CPSs. Asset monitoring and autonomous air vehicle application can be classified as the hybrid CPSs. This dissertation focuses on the applications associated with the indoor category of CPSs.

Another widely recognized subcategory of CPSs is the mobile cyber-physical systems due to the increasing popularity of smart phones, equipped with sensors capable for measuring physical elements. These smart phones are widely networked and provide sufficient computational resources.

Integration of human factor component to the existing CPSs can provide multiple additional benefits from human decision making abilities, social architecture, cognitive and sensing skills. In recent years, the concept of cyber-physical-social system has been proposed by various researchers as a subcategory of existing CPSs or future of CPS architecture[34],[35].
2.1.4 Challenges

The development of a functional CPS application, incorporating features mentioned in the previous section, is a challenging task. Along with these features, the CPS domain also inherits challenges from its predecessor technologies with added challenges at the interface level. The development of CPSs also faces knowledge discovery and situation awareness challenges from the complex heterogeneous physical sensors connected to them. Table 2.2 shows various challenges associated with CPS domain in three categories defined by previous researches[26],[23],[26],[20].
Table 2.2: Challenges associated with the cyber-physical domain.

<table>
<thead>
<tr>
<th>Physical level challenges</th>
<th>Cyber level challenges</th>
<th>Integration level challenges</th>
</tr>
</thead>
<tbody>
<tr>
<td>Robustness &amp; reliability</td>
<td>Uncertainty</td>
<td>Real-time performance</td>
</tr>
<tr>
<td>Automation &amp; hybrid systems</td>
<td>Abstractions</td>
<td>Synchronization in space &amp; time</td>
</tr>
<tr>
<td>Sensor failures</td>
<td>Interoperability</td>
<td>Security, safety, verification</td>
</tr>
<tr>
<td>Network connectivity</td>
<td>Scalability</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Entity identification</td>
</tr>
</tbody>
</table>

The primary physical level challenges of the CPSs are associated with generating continuous, failure proof and real-time sensor. These challenges are also associated with providing communication mechanism between physical and cyber components. To fulfill these requirements, the CPSs should provide methodologies to provide synchronization between event centric and time based systems for feedback control. The communication infrastructure should provide sufficient resources for data transfer and discovery of physical components. Each of these physical level challenges is associated with separate domain of engineering such as embedded systems, control systems, sensor fusion, communication and networking. These challenges are domain, application and priority specific.

The connectivity architecture between cyber and physical component provides unique challenges for the CPSs. The interface between cyber and physical components requires spatial and temporal synchronization. In some cases, applications require real-time duplex communication between these components for sensor perception and
feedback control. The example scenario, explained and developed in this dissertation, provides real-time connectivity between the sensor platform and the computation mechanism responsible for event identification.

The dissertation focuses on challenges associated with cyber or the application aspect of the CPSs. The main goals of the cyber level components are to discover knowledge from the physical sensor data and provide applicable actions for the feedback control. The challenges for the cyber component are to develop a methodology to identify physical and computation abstraction, provide strategies to handle uncertainties and interoperability between systems. The designed application should also provide scalability from moderate level to complex models of CPSs. In this dissertation, efforts have been made to provide solutions for each of the challenges associated with the cyber-physical domain.
2.2 CPS architecture

This section discusses the traditional architecture of embedded systems and its evolution to the current cyber-physical system.

2.2.1 Traditional architecture of embedded systems

Basic embedded system architecture consists of sensors, actuators and a microcontroller unit as shown in Figure 2.4. An embedded system can have single or multiple sensors and actuators interacting with physical world[36]. Although some embedded systems may contain multiple computational units, usually it has single microcontroller unit providing basic computational functionally and interfaces to interact with sensor and actuators. Common embedded systems lack complex computation capabilities in terms of knowledge discovery and event identification.

![Figure 2.4: Architecture of traditional embedded systems.](image-url)
The predecessor of the CPSs such as RFID technology and wireless sensor networks contains similar architecture. Similar to the embedded system architecture, these technologies have networked connectivity between nodes but provide lower computation capabilities.

### 2.2.2 System level CPS architecture

![Cyber-physical system architecture](image)

**Figure 2.5: Cyber-physical system architecture.**

By definition, a CPS incorporates physical world and cyber component using communication infrastructure. Each of these physical, cyber and communication components can have heterogeneous architecture specific to application requirements. The physical level architecture may display various types of sensors, actuators,
controllers and their interface to each other. The communication infrastructure can have different forms of networking topologies and connection nodes. On the cyber level, the architecture can have implementation of numerous reasoning algorithms utilizing application specific domain knowledge. Figure 2.5 provides generalized system architecture consisting of nominal but necessary blocks from each cyber, physical and communication components [25],[37]. As shown in Figure 2.5, the physical level components interact with the real world environment via sensor and actuator unit. These physical level components offer basic computation capabilities by providing an interface to these units and their connectivity with the networking infrastructure. The communication infrastructure provides tight coupling between the physical level and the cyber components. The cyber or application level components provide reasoning and decision making mechanism. At each component level, the original physical context is converted into higher-level abstractions. The concept of abstractions is explained later in this chapter.

2.2.3 CPS versus Internet of Things (IoT)

First introduced in the seventh edition of International Telecommunication Union (ITU) report, “The Internet of Things (IoT)” represents networked and interconnected everyday objects and devices, called “Things”, to create potential products and services of future[38]. The IoT is the next generation ubiquitous or pervasive computing concept and successor of RFID technology, which provide virtual representation of physical objects in the Internet like structure. The Things do not only represent desktop or mobile computing platforms, but also characterize tiny objects
with computation capabilities to interact with the physical world and collect sensory information[39][40].

IoT and CPS are similar concepts synchronously being developed by different communities, ubiquitous computing and embedded systems, respectively[27]. Based on its foundation from ubiquitous computing and RFID technology, The IoT concentrates on the communication infrastructure for connecting physical objects using networking platforms. The CPS focuses on the sensing and control aspects of physical objects as its root lies in embedded and real-time systems[41].

The CPS concept requires 3Cs, communication, controls and computation, as basic defining components, making control of physical objects a mandatory requirement. In the IoT, interconnected physical sensing objects interact with the cyber world but do not necessarily have implementation of feedback control mechanism at the physical level. Even complex computation at the physical level is not a necessary requirement for an IoT application. In conclusion, the IoT have ambiguous boundaries and specifications for system level components compared to the cyber-physical system. Due to these reasons, the CPS is considered as subdomain of the IoT.

In summary, although the IoT and the CPS are different in terms of defining features both represent analogous concept of interconnecting physical sensing domain with cyber world from the fundamental application point of view. As mentioned in the challenges subsection, the focus of this research is on the challenges associate with the cyber part of the cyber-physical systems. Due to focus on the interconnection and networking part, the challenges associated with the IoT domain are similar to the
challenges being considered for this research. Therefore, the situation awareness
framework proposed in this dissertation can be simultaneously implemented in an IoT
application.
2.3 Situation awareness (SA)

2.3.1 Introduction

Proposed by Endsley [42], the earliest and widely accepted definition of situation awareness as, “perception of the elements in the environment within a volume of time and space, the comprehension of their meaning and the projection of their status in the near future.”. This early framework proposed three main components of the situation awareness problem: (1) Perception (2) Comprehension and (3) Projection. The first step perception involves the collection of sensory information such as status, attributes and dynamics from related environment. The next step, comprehension, utilizes the collected perceptions and the background knowledge about the event to comprehend the meaning or significance of the perception data by identifying an event or a situation. The last step, projection, involves extrapolating comprehended knowledge to identify the future state of the current event. In other word, primary aspect of situation awareness system is to comprehend events, which will require projection of actions or
projection of the future state of the environment. The sensor perceptions can infer to multiple entities in the environment, but not all of them are responsible for the comprehension of the situation. For the example scenario described in Chapter 1, a fire at the fireplace and a fire at the chair are detected via reasoning over high temperature and excessive carbon dioxide perceptions. In a situation awareness system selection for the situation, among all ongoing events in the environment, is application specific. In the case of example scenario, the situation to be identified is the house fire, which can be projected as the future state of the fire at the chair. The definition of each components of situation awareness framework varies with the requirements, goals and objective of the application.

2.3.2 Challenges with traditional SA approaches

The traditional situation awareness systems lack robustness in decision making process due to the limitation of human information processing capabilities. Various situation awareness challenges are summarized and classified by researchers in recent years[43], [44]. In this dissertation, emphasis is on solving the following challenges:

- **Information overload**: The rate of change of sensory information can overpower the data apprehending and decision making abilities of the operators.

- **Attention narrowing**: Multitasking ability of an operator can suffer as a result of focusing only on a specific type of events.

- **Requisite memory trap**: The situation awareness system should reduce load on the operator by reducing the information to be held in memory.
• **Complexity creep**: Complex sensor streaming information and context classification can influence the operator to produce erroneous situation comprehension.

Traditional SA approaches require the operator as a human component to reason over the sensor perceptions. The challenges described above are associated with the decision-making ability of the operator. These challenges can be solved by implementing the concept of abstractions for sensor observation and events comprehension. By utilizing domain knowledge, an autonomous reasoning algorithm can use relationship between these abstractions to infer an event or list of events as candidates for the situation comprehension.
2.4 Defining situation awareness in indoor CPSs

The role of each component in SA may vary for different domains and application. In medical diagnosis domain, dizziness can be considered as a perception while low blood sugar as comprehension of the situation. In system interacting with the physical environment, sensors reading are considered as perceptions while the event such as fire is a comprehension of the situation. In a CPS implementation, multiple heterogeneous sensors are used to interact with the physical environment. Therefore, the perception process in CPSs is associated with acquiring physical sensor information, which is in the form of numerical numbers and not in the form of vogue concepts. Since these perception sources are in a large number, the number of events that can be detected is also high. For a specific CPS application, not all events can lead to comprehension of a situation. In the case of indoor CPSs, the spatial information from the sensor can also provide vital information towards efficient comprehension of the situation from identified events.

In summary, SA in indoor CPSs can be described as comprehension of application specific situation from sensor perceptions collected from the physical environment along with their indoor spatial information. The situation awareness framework should also provide interoperability between multiple systems attempting to comprehend different situation. The projection of the future state of that current event can be predicted by implementing similar methods used to identify comprehensions from the perceptions.
2.5 Contexts and context awareness

2.5.1 Defining context

Context is an ancient concept studied by philosophers and linguists. In recent years, popularity of technologies such as ubiquitous and pervasive computing has attracted computer science researcher towards this abstract concept of Context and Context awareness. By Oxford English Dictionary definition, context is defined as “the circumstances that form the setting for an event, statement, or idea, and in terms of which it can be fully understood and assessed”. The definition and meaning of context is highly dependent upon the settings, and the settings are dynamic with respect to domains and the applications[45],[46],[47].

In the computer science domain, the concept of context can be applied to following settings: (1) Computing environment i.e. processing power, networking capacity, computation cost, etc. (2) User or conceptual environment i.e. location, collection of people and social structure. (3) Physical environment i.e. temperature, pressure, humidity, etc. From the perspective of cyber-physical systems, this setting environment can be considered as physical events generating sensory context[48]. In this dissertation location is defined as a separate concept apart from physical context, which is defined in detail later in this chapter.

2.5.2 Defining context awareness

Similar to the term context, the concept of context awareness also has its roots in the domain of linguistics. In computer science, context awareness computing term was first coined by Schilit and Theimer[49]. In that paper, the context aware computing
was defined as an application, which collects context information and adapts itself to the context. The context aware computing is now widely defined as a system which provides relevant information from the collected context and finds their relevancy with associated events. In cyber-physical system, the context awareness can be defined as a process of aggregating physical environmental context from sensors and find their association with the ongoing events. Figure 2.7 shows the collected raw physical environment phenomenon as a temperature context. The context awareness applications use this temperature context to identify the meaning of this context information in term of a context source or an event such as a fire.

![Figure 2.7: Context awareness model.](image)

**2.5.3 Context abstraction**

The process of finding events from the raw context data is difficult as the relationship between the contexts and events is complex and dynamic in terms of application requirements. For example, the temperature context can be related to other events such as normal room and heater, including fire. Also, the temperature ranges
associated with these events are different from each other. In this dissertation, for a cyber-physical system, context is considered in the form of real-time continuous sensor data from the physical environment and other categories of contexts such as computational capacity, networking capacity, etc. are out of scope.

The concept of abstraction organizes context in the form of reoccurring patterns or set associated with an event. The raw sensor information from the environment can be translated in the form of low-level abstractions, widely known in semantic web domain as qualities\cite{50},\cite{51}, \cite{52}. The context sources or associated events can be distributed in high-level abstractions, often known as entities. High temperature is a quality, which is associated with fire entity; similarly medium temperature abstraction can be explained from entity such as normal room condition. The raw sensor data can be translated into the qualities by defining abstraction ranges in the domain knowledge. For example, 200°F temperature can be categorized as high temperature assuming the range for high temperature is defined between 150 °F to 500 °F. The real challenge is in finding high-level abstractions from the calculated low-level abstractions as interpretation of high-level abstractions may depend upon multiple low-level abstractions and the correlation between these low-level abstractions. Efficient derivation of high-level abstractions can be achieved by modeling relationship rules and developing reasoning mechanism.
2.5.4 Contextual situation awareness

Situation awareness and context awareness are relatively similar concepts as both deal with providing event assessment from sensory information. While situation awareness works towards modeling and comprehending the physical environment to assist the operator, context awareness exploits environmental context to assess an event[53], [54]. The situation awareness framework is designed to be used in the command and control domain, where the operator requires specific reasoning skills to assess the situation. In CPSs, for the same context information, the meaning and structure of these reasoning mechanisms change with respect to other applications.

This dissertation incorporates the concept of contextual situation for cyber-physical application. In a CPS application, physical context information, associated with the situation to be monitored, is defined as contextual situation[3]. The environment can have multiple context information, but the contexts, responsible for the specific
event, can be classified as situational context. For example in the motivational scenario, in Chapter 1, the environment has various contexts such as temperature, carbon dioxide, heart rate, body temperature, etc. For an application focusing on cardiac arrest situation, the heart rate and body temperature contexts can be classified as situational context. Similarly, for an application detecting house fire, the temperature and carbon dioxide level can be classified as situational context. The classification of a context as a situational context is totally dependent upon the application and its reasoning rules.

In summary, this dissertation utilizes situational context awareness concept to autonomously identify the appropriate situation by exploiting physical context information from the environment, associated with the situation. The context information in terms of location can assist the contextual situation awareness results to further optimize the event identification result, which is explained in Section 2.6.
2.6 Location Awareness: Complementing the context awareness

Earlier computing applications, utilizing spatial information, were limited to monitoring office spaces and employees[55],[56]. Recent developments in localization technologies, particularly indoor localization, have empowered location based applications for mobile robot tracking, patient monitoring and military ad hoc networks[57], [13].

Location awareness can be defined as the ability of a system to determine its spatial information. Although the location is a type of context information, earlier ubiquitous and mobile computing applications were built to utilize location as only or primary context information. Due to this reason, the location-based service has sprung as a separate application domain. In recent years, advancements in sensors and mobile technology have enabled integration of the physical environment monitoring sensors on mobile and ubiquitous devices. Although, in linguistic semantics, location is a type of context, location awareness and context awareness are being considered as two separate domains. The location awareness deals with identification of spatial information of an object or an event while context awareness utilizes physical context information to classify events. In the concept of situation awareness, where context is part of a situation, the objects in the physical environment have spatial information and are associated with the situation. These objects are possible candidate of being context source for a situation. By exploiting the relationship between these objects and a situation, spatial information can assist in determining the context source. In other
words, the location awareness and context awareness are complementary to each other in extracting the situation[58], [59].

In the motivation scenario in Chapter 1, the context awareness can assist in extraction of entities such as fires, abnormal heart rate, etc. The location awareness can complement the context awareness by providing the spatial information regarding the sources of the context responsible for those entities, which can lead the system towards optimization of the entity extraction results and provide efficient situation assessment. Figure 2.9 displays the relationship between context and location awareness and the situation via a pyramid diagram.

Figure 2.9: Situation comprehension using context and location awareness.
2.7 Summary

In summary, the chapter defined various components and concepts associated with this dissertation. Although, the meaning of each of these components varies depending upon the research domain, they are explicitly defined for this research as following.

**Cyber-Physical System (CPS):** is a complex system tightly coupling physical world objects using computation, communication and control interfaces.

**Environment:** is defined as a physical environment consisting of various objects responsible for a situation i.e. room, building, car, etc.

**Context / Quality Type:** is a physical phenomenon in environment, measured using sensors, and product of an event i.e. temperature, heart rate, carbon dioxide, etc.

**Event / Entity / Feature / Context source:** is defined as a phenomenon contributing to various physical contexts in the environment. An environment can have multiple events, entities or features but not all of them can be classified as a situation because of application focus e.g. fire at chair, fire at fireplace, abnormal heart rate on bed, stove on/off, etc.
**Situation:** is defined as a focus event specific to a domain application. A CPS application can have multiple focus events to be observed such as house fire and heart attack.

**Situation Awareness (SA):** is defined as a comprehension of a situation from perception of various entities in the environment, obtained from the observations of the physical context.

**SA in indoor CPS:** is a process of identifying a situation in indoor environment utilizing context and spatial information. It deals with the context or sensory information originated from the situation in the form of physical phenomenon.

**Observation:** is a process of measuring aspect of the physical environment. An observation contains sensory, temporal or spatial information of the context.

**Quality / low-level context Abstraction:** is a concept, which represents the raw context information in relative set or range. A context abstract or a quality can be derived from reoccurring patterns or a range. These ranges are a function of the situations being observed and vary with respect to different situations. For example, high temperature, low Carbon Dioxide, high heart rate, etc.

**Context Awareness (CA):** is a process of comprehending the meaning of the physical context in terms of events or entities.
**Location:** is the spatial information of an object represented in the form of Cartesian or Geo coordinates.

**Point of Interest (POI) / Object:** is defined as a physical object in the environment and is associated with the physical context source or entities.

**Location Awareness:** can be defined as process of identifying objects from raw spatial information and their relationship with the ongoing events.
3 Contextual situation Awareness via Fuzzy Abductive Reasoning

This chapter presents methods for obtaining contextual situation awareness via event identification from raw physical context associated with events. The chapter presents fuzzy abductive and semantic web based approach to handle challenges such as uncertainty in the context and interoperability. Section 3.1 describes the domain knowledge base representation techniques and terminology used to describe the concepts. Section 3.2 compares deductive and abductive reasoning techniques with the importance of abductive reasoning in the situation awareness applications. Section 3.3 explains the concept of crisp abstraction assisted observation and perception process for event extraction using abductive reasoning while Section 3.4 describes challenges associated with this approach. Section 3.5 presents the concept of fuzzy context abstractions and provides a methodology to use these abstractions for fuzzy abductive reasoning based event extraction with certainty confidence. Section 3.6 presents the semantic web based annotation and modeling approaches utilizing Semantic Sensor Network (SSN) and the domain ontology to achieve interoperability. The evaluation of the proposed context based situation awareness method on a simulate fire scenario is provided in Section 3.7 and the summary of the chapter in Section 3.8.
3.1 Domain knowledge and semantic concepts

The context awareness application requires domain knowledge base (DKB) consisting of concepts such as qualities and entities with their mutual relationship for efficient situation assessment[60]. These concepts and relationships are obtained from the domain experts and are subjective to the available situation contexts and events to be determined.

![Image of domain knowledge base](image)

**Figure 3.1: A graphical representation of domain knowledge base containing concept relationships.**

The DKB can be represented as a bipartite graph as shown in Figure 3.1. The bipartite graph consists of the situational entities such as fire, dry-ice, heater, etc. with their relationships to the associated qualities. The DKB depicted in figure 3.1 consists of primitive association and may not provide evidence to the effective situation in advance applications. A DKB is required to provide efficient assessment of the situation from the environmental context. Perera et al. presented a data driven methodology to enrich
DKB to compensate incompleteness by focusing on populating domain relationship and finding missing components[61]. This dissertation provides a step towards achieving effective context awareness by utilizing domain knowledge obtained from similar methods.

Cory et al. developed the IntellegO ontology to support hypothesis based reasoning for obtaining entities from the available DKB[62]. The dissertation utilizes the IntellegO, which models the crisp abstraction concepts and extend it to include fuzzy abstraction concepts, later introduce in this chapter. The subset of concepts and relationships inherited from the IntellegO are described as following (note: io prefix is used to denote concepts from the IntellegO ontology).

*io:entity*: formalizes concept of event or entity in the environment e.g. fire.

*io:quality*: is inherited property of *io:entity* e.g. high temperature, extensive CO₂.

*io:inheresIn*: is a relationship between *io:quality* and *io:entity*.

*io:qualityType*: formalizes a category of *io:quality* or the context type e.g. temperature.

*io:hasType*: is relationship between *io:quality* and *io:qualityType*.


3.2 Deductive versus Abductive reasoning

Deductive reasoning process has been extensively used for the embedded system, the wireless sensor network and the health care domains for monitoring of the environment[63][64]. Deductive logic is a hierarchical process of reasoning to reach the logical conclusion when every criterion defining the concepts is met. Deductive reasoning can be explained from the following rules.

\[
\text{IF event is FIRE THEN temperature is HIGH and CO}_2 \text{ is HIGH;}
\]

\[
\text{IF event is DRY ICE THEN temperature is LOW and CO}_2 \text{ is HIGH}
\]

where, the FIRE is only detected when the observation provides high temperature and CO\textsubscript{2} context. In the absence of any observation, the FIRE cannot be determined.

Abductive reasoning process is a hypothesis-based approach to reach the logical conclusion towards the best explanations of the events from the observed effects. The abductive reasoning process can be explained by the following set of chain rules:

\[
\text{IF temperature is HIGH THEN events are FIRE, ROOM HEATER;}
\]

\[
\text{IF CO}_2 \text{ is HIGH THEN events are FIRE, DRY ICE}
\]

where, the high temperature observation provides evidence for the FIRE and the ROOM HEATER. If the high CO\textsubscript{2} observation is obtained, the FIRE can be concluded as the event satisfying both rules.
In the cyber-physical systems where numerous numbers of heterogeneous embedded systems are networked, the probability of data inconsistency due to faulty and malicious sensors and data loss due to communication interruptions is significant. Due to these reasons, a situation awareness application in the CPS domain can suffer limitations in implementation of deductive reasoning mechanism. As also describe in Section 3.1, the concept of io:entity explains the observed io:quality and similarly the observed io:quality provides an indication to the io:entity[65]. In other words, the situation awareness application can be benefited in terms of identifying observation errors through the implementation of abductive reasoning approach. From CPS prospective, reconstruction of the current state of the environment and identification of responsible events from the raw sensor data requires abductive reasoning process. This dissertation exploits the DKB to generate hypothesis to infer events and utilizes the abductive reasoning methods to test these hypothesis on the observed effect with the help of the IntellegO ontology.
3.3 Abductive reasoning with crisp abstraction

The method of event extraction consists of the observation process and perception process formalized in the IntellegO as `io:observationProcess` and `io:perceptionProcess`, respectively. The observation process deals with obtaining `io:quality` abstractions from the raw sensor data while the perception process utilizes `io:quality` to infer `io:entity` as described in Figure 3.2.

![Observation and perception processes](image1)

**Figure 3.2: Observation and perception processes.**

![Graphical representation of reasoning rules with crisp abstractions](image2)

**Figure 3.3: Graphical representation of reasoning rules with crisp abstractions.**
Figure 3.3 represents the DKB containing \textit{io:quality} abstraction with their ranges and their association with the \textit{io:entity}. The DKB also includes the \textit{io:quality} as a function of appropriate \textit{io:qualityType}.

\subsection*{3.3.1 Observation process}

The physical component of the CPS collects raw sensory context and sends it to the cyber component to discover knowledge in terms of the situations. This sensor data generally is in the form of a digital value or continuous stream with their unit of measurement. In order to attain this, first the raw sensor information needed to be transformed into meaningful thematic \textit{io:quality} abstractions. For example, the observation of 60 °F in thematic form can be depicted as \textit{LowTemp} low-level \textit{io:quality} abstraction. This can be achieved by implying range or pattern based rule on raw sensor data. Barnaghi et al. presented Symbolic Aggregate Approximation (SAX) based pattern construction method to obtain low-level abstraction from the streaming sensor data\cite{51}.

The set of \textit{io:quality} from each of observations $o_1, o_2, \ldots, o_n$ can be obtained from Equation (3.1). For example, observation $o_1$ contains the \textit{HighTemp} and $o_2$ contains the \textit{LowCO2} qualities in terms of the temperature and CO2 \textit{io:qualityType}. These sets are then used to infer \textit{io:entity} by exploiting the \textit{io:inheresIn} relationship for these qualities.

\begin{equation}
\textit{io:quality} \equiv \exists \textit{io:observedQuality}.\{o_1\} \sqcup \ldots \sqcup \exists \textit{io:observedQuality}.\{o_n\}
\end{equation}

(3.1)
3.3.2 Perception process

The explanatory entity is the entity that explains the set of the observed qualities from the observation process. For the observed qualities $q_1, q_2, \ldots, q_n$, the explanatory entity can be obtained from equation (3.2).

$$\text{ExplanatoryEntity} \equiv$$

$$\exists \text{io:inhereIn.}\{q_1\} \cap \ldots \cap \exists \text{io:inhereIn.}\{q_m\}$$

(3.2)

For example, HighTemp quality is associated with Fire and RoomHeater entities via io:inhereln relationship while HighCO2 is associated with Fire and DryIce entities. Implementation of equation (3.2) on these results provides Fire as the explanatory entity for the situation.
3.4 Making a case for fuzzy context abstractions

Accuracy of the crisp abstraction approach used in the previous method suffers from the imprecise sensor readings and the insufficient domain knowledge. In the real world applications, unknown context sources present in the environment alter the consistency of the context information obtained from the real situation making the crisp abstraction approach unreliable. For example, various context sources not modeled in the DKB such as people, heater, etc. can generate temperature and carbon dioxide contexts, which may affect the inference of the fire situation. Similarly, in case of heart rate context, crisp abstraction approach described in the previous section cannot sufficiently model the unknown parameters in the background knowledge such as the age of the patient, sex and age.

The fuzzy logic and fuzzy set theory introduced by Zadeh have been widely used in the controls systems, the embedded system and the automation domains to handle ambiguity in the sensor information [66] [67]. The fuzzy logic approach converts the crisp sensor value into a linguistic set with certainty degree associated with that set. For event detection applications in the wireless sensor networks domain, the fuzzy logic approach has been successfully implemented by various researchers with the improved accuracy on the crisp threshold based logics[68][10]. The dissertation employs the fuzzy logic based approach to solve the challenges describe for the crisp abstraction approach as it reason over the ongoing events and provides certainty confidence of the existing events rather than probability based approaches which deal with predicting the future state of the events.
3.5 Fuzzy abductive reasoning with semantic context abstractions

The fuzzification process translates an observation containing crisp sensor value into membership degree via applying the appropriate membership function. The membership denoted as $\mu$ can have different shapes such as triangular, trapezoidal and Gaussian according to the domain knowledge and the application requirements. Figure 3.4 shows fuzzy sets for the carbon dioxide quality type with trapezoidal as preferred shaped of the function. For observation (a) with 900 ppm of carbon dioxide value, the membership or certainty degree for LowCO$_2$ and HighCO$_2$ thematic abstractions can be calculated by equation (3.3).

![Figure 3.4: Fuzzy abstractions and membership function $\mu$.](image)

\[
\mu_{\text{LowCO}_2}(a) = \frac{1200 - 900}{400} = 0.75
\]

\[
\mu_{\text{HighCO}_2}(a) = \frac{900 - 800}{400} = 0.25
\]

(3.3)
The process of abductive reasoning on fuzzy abstractions is formalized as fuzzy abductive reasoning to distinguish it from the abductive reasoning on crisp abstractions. The fuzzy abduction has been used in fault diagnosis application to derive fuzzy sets for hypothetical explanation of the events[69]. This dissertation attempts to solve the situation awareness problem by diagnosing qualities from the sensor data obtained from ongoing events, therefore, the fuzzy abductive reasoning is selected as the primary approach to deal with fuzzy abstractions derived from the context.

3.5.1 Observation process and fuzzy semantic abstractions

Due to the disjoint characteristic of the crisp sets, an observation from a context source can only infer to single quality e.g. 39 °F and can be only translated to LowTemp and not HighTemp. In case of fuzzy abstractions, the observation can infer to multiple abstractions with associated certainty degree as described in equation (3.3). The phenomenon can be formalized via following proposition.

\[\mu\]

\[\begin{align*}
  &\mathbf{0} &\mathbf{a} &\mathbf{1} \\
  &\mathbf{x_1} &\mathbf{x_2} \\
\end{align*}\]

\[\mu \uparrow\]

Figure 3.5: An observation ‘a’ in fuzzy range of qualities x1 and x2.
Proposition: Explained \textit{io:entity} from \textit{io:qualityType} is the union of \textit{io:entity} explained from the set of \textit{io:quality} associated with that \textit{io:qualityType} for an observation where these \textit{io:quality} are represented by adjacent fuzzy sets.

Figure 3.5 shows an observation (a) for quality-type X, in fuzzy region between qualities x1 and x2. The associated qualities x1 and x2 can be obtained from the observation (a) via equation (3.4) using observed quality-type property.

\[ \textit{io:quality} (a) \equiv \exists \textit{io:observedQualityType}. \{X(a)\} \]

(3.4)

where, qualities explained by the appropriate entities can be extracted via equation (3.5).

\[ \textit{io:entity}(x1) \equiv \exists \textit{io:inheresIn}. \{x1(a)\} \]
\[ \textit{io:entity}(x2) \equiv \exists \textit{io:inheresIn}. \{x2(a)\} \]

(3.5)

From proposition, the explanatory entities from the quality-type X are union of the entities inferred from qualities x1 and x2. Therefore, the explanatory entities from the observation (a) can be obtained as described in equation (3.6) in the case where (a) is in fuzzy region.

\[ Entity(a) = Entity(x1(a)) \cup Entity(x2(a)) \]
\[ \textit{io:entity}(a) \equiv \exists \textit{io:inheresIn}. \{x1(a)\} \cup \exists \textit{io:inheresIn}. \{x2(a)\} \]

(3.6)
3.5.2 Perception process with fuzzy abstractions

The observation process with fuzzy abstractions provided the qualities associated the observed sensor data. Figure 3.6 shows the extension of the DKB by defining membership functions for qualities and their relationships with the entities.

![Diagram showing fuzzy context abstractions for temperature and CO2]

*Figure 3.6: Graphical representation of rules with fuzzy context abstractions.*

From the observation process, the set of observations \( o = \{o_1, o_2, \ldots, o_n\} \) is obtained with the associated \( \text{io:qualityType} \ k_t = \{k_{t1}, k_{t2}, \ldots, k_{tn}\} \). The observed \( \text{io:quality} \) from these \( \text{io:qualityType} \) are \( k_{t1} = \{q_{t11}, q_{t12}, \ldots, q_{t1m}\}, k_{t2} = \{q_{t21}, q_{t22}, \ldots, q_{t2k}\}, \ldots, \) and \( k_{tn} = \{q_{tn1}, q_{tn2}, \ldots, q_{tnp}\} \). The \( \text{io:entity} \) from these observation can be obtained using equation (3.7).
The certainty degree of the events are calculated as the separate process once the \textit{io:entity} and the explanatory \textit{io:quality} are obtained. The certainty degree for \textit{io:entity} is obtained by performing standard fuzzy intersection operation on the membership function of the obtained \textit{io:quality}. The fuzzy standard fuzzy intersection operation is the minimum operation between respective membership functions[66].

\[
\mu_{entity}(a) \equiv \mu_{q_{11}}(o_1) \wedge ... \wedge \mu_{q_{nn}}(o_n) \\
\equiv \min(\mu_{q_{11}}(o_1), ..., \mu_{q_{nn}}(o_n))
\]

(3.8)

The fuzzy abduction which leads to single explanation concluding the situation is called the \textit{simple} fuzzy abduction[70]. The analysis result containing multiple explanations with certainty degree is called the \textit{composite} fuzzy abduction. In \textit{composite} case, further analysis is required to obtain the appropriate event by setting a cut off limit on certainty degree. For this case, discrimination based approach can also be used to further reduce the number of explanations[62], [71].
3.6 Semantic sensor web integration

The complexity of reasoning rules for the event identification method utilizing fuzzy abstractions, proposed in the previous section, grows exponentially with the addition of context sources to the physical component of the CPS. In case of the traditional rule based implementations, any modifications in rules can lead to extensive changes in the implemented system. The issue of interoperability becomes significant when heterogeneous physical components try to provide sensor information for the reasoning mechanism.

The Semantic web, introduced by W3C to formally define the meaning of the information on the internet, can provides more expressive representation, analysis and reasoning for sensor information. Lin et al. and Ryan et al. presented different semantic web based approach to model system components of the CPS using the semantic web based technology for water distribution and health care applications, respectively[72][73]. Although these approaches provided modeling methods, they failed to address event identification and interoperability issues. The Semantic Sensor Web (SSW) includes the standards based approach to represent sensors and sensor data with also enabling semantic web based ontologies to represent and reason over this data[74][75]. The SSW also provides support for modeling flexibilities for complex rules, interoperability via standards and autonomous and intelligent decision making. The dissertation utilizes the SSW assisted methodology to integrate semantic web with the proposed event identification framework as described in Figure 3.7.
Figure 3.7: An event extraction framework from contextual data aided by ontologies.

The framework utilizes Semantic Sensor Network (SSN) ontology for annotation of the raw sensor data in to the observations. The SSN ontology, developed by W3C provides the standard towards formally modeling sensor devices, sensor platforms, knowledge of the environment and observations[76] [77]. The SSN provides a foundation in the direction of achieving interoperability between the interconnected CPSs. The graphical representation of the subset of SSN used in the proposed framework with examples is described in Figure 3.8.

The domain ontology contains the application specific terminology describing concepts in the DKB and extends the SSN ontology. The domain ontology and the fuzzification rules containing details regarding the fuzzy context abstraction are used to obtain the low-level abstractions in terms of qualities and their membership functions.
The ontology containing fuzzy inference rules is used to infer the entities from the obtained qualities as the extension of the IntellegO ontology described in Section 3.3. To enable the inference process, a mapping between the SSN and the IntellegO ontology is required, also known as ontology alignment. The mapping between SSN concept of \textit{ssn:property} and \textit{ssn:features} with IntellegO concepts \textit{io:quality} and \textit{io:entity} is shown in Figure 3.9. The prefix \textit{ssn} verbalizes the concepts from the SSN ontology.
Implementation of these mapping rules enables reasoning over the raw sensor data for the event identification via the observation and perception process described in Section 3.5.

*Figure 3.9: Ontology alignment between SSN and IntellegO.*
3.7 Evaluation

The evaluation of the fuzzy abductive reasoning approach was performed on an indoor fire scenario consisting two distinct fires simulated at different locations with additional context sources in the environment. A platform mounted with an infrared-temperature and a carbon dioxide sensor was used to obtain physical sensor data from the environment, originated from the context sources, with the goal of extracting the fire event. Figure 5.10 shows the experimental setup and the path of the mobile platform used to collect the sensor data.

Figure 3.10: The experimental setup containing two fire events and path of the mobile platform in the indoor environment.
The observation collected at the location (a) in the vicinity of the fireplace is selected to explain the crisp and fuzzy reasoning approaches. The observation (a) contained 119.2 F and 1400 ppm as the temperature and CO₂ context, respectively.

- **Crisp abductive reasoning:**
  
  HighTemp and HighCO₂ qualities were observed at the location (a) using the observation process described in Section 3.3.1. Fire entity was extracted using the perception process described in Section 3.3.2 and crisp reasoning rules explained in Figure 3.3. Equation (3.9) shows the perception process via utilizing HighTemp and HighCO₂ qualities.

  \[
  \text{io:entity} \equiv \exists \text{io:inheresIn.\{HighTemp\}} \cap \exists \text{io:inheresIn.\{HighCO₂\}} \\
  \equiv \{\text{Fire,DryIce}\} \cap \{\text{Fire,RoomHeater}\} \\
  \equiv \{\text{Fire}\}
  \]

  (3.9)

- **Fuzzy abductive reasoning:**
  
  This approach utilized the fuzzy abstraction and reasoning rules displayed in Figure 3.6 to obtain qualities with membership function from the observation (a). The HighTemp and LowTemp qualities were obtained from the temperature quality-type with membership function of 0.98 and 0.12, respectively while HighCO₂ quality with membership function 1 was obtained from the carbon dioxide observation as displayed in equation (3.10). The perception process
described in Section 3.5.2 provided Fire and DryIce (equation 3.11) entities with certainty confidence 0.98 and 0.12, respectively (equation 3.12).

\[ \mu_{\text{HighTemp}}(a) = 0.98, \mu_{\text{LowTemp}}(a) = 0.12, \mu_{\text{highCO}_2}(a) = 1, \mu_{\text{LowCO}_2}(a) = 0 \]  

(3.10)

\[ \text{io:entity} \equiv \exists \text{io: inheresIn.} \{\text{HighTemp}\} \cup \exists \text{io: inheresIn.} \{\text{LowTemp}\} \]
\[ \cap \{\exists \text{io: inheresIn.} \{\text{highCO}_2\}\} \]
\[ \equiv \{\text{Fire, DryIce} \cup \{\text{NormalCondition, RoomHeater}\}\} \]
\[ \cap \{\text{Fire, DryIce}\} \]
\[ \equiv \{\text{Fire, DryIce}\} \]  

(3.11)

\[ \mu_{\text{Fire}}(a) = \mu_{\text{HighTemp}}(a) \land \mu_{\text{highCO}_2}(a) \]
\[ = \min(0.98,1) \]
\[ = 0.98 \]

\[ \mu_{\text{DryIce}}(a) = \mu_{\text{LowTemp}}(a) \land \mu_{\text{HighCO}_2}(a) \]
\[ = \min(0.12,1) \]
\[ = 0.12 \]  

(3.12)
The process of extracting entities and certainty degree from observed qualities was performed for crisp and fuzzy abductive reasoning approaches at 50 consecutive locations on the mobile platform path. True positive (TP), true negative (TN), false positive (FP) and false negative (FN) results were obtained in reference to Fire entity at those points. Table 3.1 and 3.2 show these results with respect to crisp and fuzzy abductive reasoning approaches, respectively.

**Table 3.1: Experimental results from crisp abductive reasoning.**

<table>
<thead>
<tr>
<th>Fire (crisp reasoning)</th>
<th>Negative (estimated)</th>
<th>Positive (estimated)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Negative (actual)</td>
<td>TN: 32</td>
<td>FP: 3</td>
</tr>
<tr>
<td>Positive (actual)</td>
<td>FN: 4</td>
<td>TP: 11</td>
</tr>
</tbody>
</table>

**Table 3.2: Experimental results from fuzzy abductive reasoning.**

<table>
<thead>
<tr>
<th>Fire (fuzzy reasoning)</th>
<th>Negative (estimated)</th>
<th>Positive (estimated)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Negative (actual)</td>
<td>TN: 34</td>
<td>FP: 1</td>
</tr>
<tr>
<td>Positive (actual)</td>
<td>FN: 2</td>
<td>TP: 13</td>
</tr>
</tbody>
</table>

The efficiency of these reasoning approaches was obtained with respect to accuracy, precision and recall using equation (3.13) - (3.15). The fuzzy approach provided 8 %, 14.28 % and 13.33 % improvement compared to crisp approach for accuracy, precision and recall results, respectively.
Table 3.3: Evaluation of crisp and fuzzy abductive reasoning approaches for detecting indoor fire entity.

<table>
<thead>
<tr>
<th>Reasoning approach</th>
<th>Accuracy</th>
<th>Precision</th>
<th>Recall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crisp abductive reasoning</td>
<td>86 %</td>
<td>78.57 %</td>
<td>73.33 %</td>
</tr>
<tr>
<td>Fuzzy abductive reasoning</td>
<td>94 %</td>
<td>92.85 %</td>
<td>86.66 %</td>
</tr>
</tbody>
</table>

In the simulation environment, the raw sensor data obtained from the temperature and carbon dioxide sensors is displayed in Figure 3.11. The figure illustrates that the raw sensor data, presented to the operator in real-time continuous format, cannot decisively provide evidence for an entity. The graphical representations of extracted Fire entity from the environment context compared to the actual simulated fire at those points are displayed in Figure 3.12 and 3.13. The fuzzy abductive reasoning approach utilized 0.5 certainty degree cut off to identify Fire as the primary candidate for the situation. The cut off range can be modified according to the application requirement.
Figure 3.11: Raw sensor data from temperature and carbon dioxide sensors on the mobile robot.

Figure 3.12: Comparison of extracted fire entity from crisp abductive reasoning with the actual fire entity in the experiment.
Figure 3.1: Comparison of extracted fire entity from fuzzy abductive reasoning with the actual fire entity in the experiment.

Figure 3.14: Crisp and fuzzy abductive reasoning results for the indoor fire experiment.
3.8 Discussion

The proposed event extraction approach from the contextual information is the first stage of the comprehensive situation awareness framework. This stage consists of a fuzzy abductive reasoning method to explain entities in the environmental with certainty confidence. The chapter also presented methods to incorporate semantic web based modeling and reasoning approaches to provide interoperability between interconnected cyber-physical systems. The extracted entities from contextual situation awareness component can be further filtered to achieve effective assessment of the actual situation via utilization of the spatial information. Next chapter, discuss a novel indoor localization algorithm to obtain accurate spatial information towards the process of attaining optimized situation comprehension.
4 An Algorithm for Accurate Indoor Localization

Accurate indoor positioning system (IPS) is a critical factor in improving overall situation awareness framework for an indoor cyber-physical system and is a significant contribution of this dissertation research. This chapter explains the necessity of an accurate indoor localization algorithm in section 4.1. Section 4.2 describes various related work in the domain of indoor positioning. Section 4.3 introduces “The Cricket”, a wireless sensor network (WSN) node developed at MIT, with the software and hardware architectures. Section 4.4 describes the traditional ‘Time Difference of Arrival’ (TDoA) based distance estimation and position approximation schemes for WSN. Section 4.4 also describes the disadvantages associated with TDoA method and proposes a requirement of an improved distance estimation algorithm. Section 4.5 proposes an algorithm based on received signal strength indicator (RSSI) and TDoA fusion to overcome difficulties faced by traditional algorithms. Section 4.6 illustrates the simulation results obtained from the proposed algorithm and finally Section 4.7 summarizes the chapter.
4.1 Making a case for accurate indoor localization

Chapter 2 described the effects of the location awareness on the situation identification results. The outdoor location awareness problem is widely researched and has mature localization techniques such as the global positioning system (GPS), cellphone tower triangulation, etc. These location techniques are ineffective in providing location for indoor objects and have larger position estimation error compared to the size of the conventional indoor objects. As the techniques such as differential GPS (DGPS) and cluster of GPS receivers can improve the overall accuracy of the GPS system, an outdoor CPS can effectively utilize the GPS for the location awareness[78]. For indoor CPSs, an accurate indoor localization system is required, independent of the GPS, due to following reasons.

(1) Limitations of traditional localization approaches in the indoor environment.

The GPS cannot be used for indoor applications due to attenuation of the RF signals as a result of their transmission through walls. Other factors affecting the GPS signals are cross correlation and interference of RF signals due to reflection of these signals from the walls and other objects[79]. The accuracy of GPS also deteriorates in urban city environment, congested forest area or where it is difficult to establish a Line-Of-Sight (LOS) link with the satellites [80]. Although DGPS provide accurate results for outdoor applications, it cannot be used in the indoor environment, as the reference receiver in the DGPS requires the LOS communication with the satellites. One of the objectives of this research is to design an effective situation awareness framework for
the partial or complete indoor CPSs. To achieve this goal, the research proposes an accurate indoor localization algorithm for the GPS denied environments. Similar to the GPS, indoor localization techniques also have to deal with indoor sources of interference and objects which block efficient transmission of signals. The proposed algorithm deals with the interferences induced by these factors and overcome them by implementing fusion and extensive training of multiple signals.

(2) Ratio of localization accuracy and the size of the objects to be identified.

The outdoor accuracy of the GPS is in the range of 10 to 20 meters due to atmospheric effects[81]. The location-based services (LBS), which use the GPS for location awareness, efficiently localize outdoor structure such as buildings, houses, playgrounds, etc. due to the large form factor of those structures compared to the accuracy of the GPS. The objects such as cars, people, mobile robots, etc. cannot be accurately pinpointed as the ratio of their size to the GPS accuracy is remarkably low. Figure 4.1 compares the accuracy of the GPS with outdoor structures. Similarly, the ratio of the object size to the accuracy of the localization system should be high in case of the indoor localization system. Figure 4.2 displays comparison of different indoor object sizes with accuracy of the GPS. The dissertation proposes accuracy of the indoor positioning system to be in the range of 20-30 centimeters for efficient localization of the indoor objects.
Figure 4.1: GPS accuracy compared with size of outdoor structures.

Figure 4.2: Comparison of indoor object on 5 meter scale.
4.2 Related work in indoor location awareness

4.2.1 Early indoor localization research

The early indoor positioning research focused on office environments to track employees and office resources. They included utilization of ultrasonic (US) signals, radio frequency (RF) signals and Infrared signals (IR) with simple devices designed to detect the presence of the objects in the environment.

The first of its kind indoor location system was ‘The active Badge’ system designed by Olivetti Research Ltd.[55]. The active badge system used a network of sensor and badges attached to staff members. The centralized location system is connected with Infrared receivers (IR), which actively communicate with IR emitters embedded to the active badges. The drawbacks behind the ‘active badge’ technology were the larger size of the badges, low accuracy of the results and their dependence on IR signals. The disadvantages of using IR based system are line-of-sight (LOS) requirement, interference by other IR signals and limited coverage range.

The ‘active bat’ system, developed at AT&T laboratories at Cambridge, used a centralized technique for distance estimation[82]. The system used collaboration of RF signal and US signals, where centralized server synchronizes the transmission sequence between nodes[56]. The ‘active bat’ system was a first approach to utilize ultrasonic signals for distance estimation. The position update ratio in the ‘active bat’ system is slow due to the centralized control system responsible for all nodes in operations such as signal transmission and distance calculations. Likewise the other early localization techniques, the ‘active bat’ system also faced challenges due to LOS requirements.
The ‘RADAR: An in-building RF-based user location and tracking system’ was developed by Microsoft Research as one of the earlier attempt to use only RF signal for distance estimation[83]. The RADAR system utilizes multiple base stations to collect empirical radio signal strength data, which provides overlapping coverage. The RADAR system provides median accuracy of 2-3 meters using empirical method. The error margin obtained from the RADAR system is almost size of an office cabin which makes the RADAR system unworthy in applications which requires accurate positioning of the indoor objects. The early RF based distance measurement and positioning techniques provided rough estimation of location or presence in the room. The US signals provides relatively good accuracy than RF signal but they are not useful in congested areas where LOS communication is unavailable or occasionally interrupted.

Due to the growing demand of RFID based technologies, the recent research in localization schemes include various types of RF signal based techniques. The RF based positioning techniques can be divided in two principal approaches: (1) received signal strength indicator (RSSI) based distance estimation and (2) angle of arrival (AoA) of radio signal.

The AoA based approaches require sophisticated arrays of antenna in order to estimate the AoA. A research paper, published by Vanderbilt University team, used rapid RF-based AoA localization for mobile sensor navigation[84]. The paper proposed by Amundson et al., 2011 utilizes radio interferometric measurement (RIM) aided by a stationary antenna array and cooperating mobile target. Another research used cooperative AoA approach for location estimation[85]. The Cooperative AoA (Co-AoA)
approach employs an AoA capable *Super-Node* to assist and improve TDoA or RSSI model based approach.

It is easier to calculate received power strength of the signal from the antenna than implementing a complex system of an antenna array. Due to this reason, RSSI based approaches are widely researched and considered appropriate for low cost localization. The prior research in RSSI based approach was concentrated toward assisting a mobile robot in navigation with the use of additional proximity sensors[86]. These prior approaches were primarily dependent upon implementation of Kalman filter and ‘Simultaneous Location and Mapping’ (SLAM) algorithms. The standard deviation of Cartesian distance estimation error achieved by this approach was 2.06m with an error of 1.01m on a single axis. These RSSI based positioning researches used RSSI to aid other positioning methods such as SLAM and Kalman filter based positioning. The RSSI based approach can be utilized in the case where accuracy of position estimation is secondary compare to the approximation of existence inside a room. Various researches tried to utilize radio signals from wireless sensor motes, Wi-Fi hot spots, Bluetooth and other wireless communication sources[87][88][89]. The stand-alone RSSI based localization techniques can only approximate position of an object or track a human by detecting the presence of that object inside a room. These techniques were highly focused on detecting the presence of the object than accurately estimating the spatial location of the object. These approaches employed radio propagation model and received power strength at the receiver to estimate the distance. The root mean square error (RMSE) in distance estimation from these researches varies in the range of 1.2 to 2.24 meters.
Calibration of radio data using the common propagation model can provide improved distance estimation results[90][91]. The entire area, being monitored, is divided in disjoint set of triangles. The anchor node estimates the set of calibration records using RSSI data and distributes the values to other sensor nodes. The distance estimation algorithm proposed in this dissertation research utilizes the principle of distributing RSSI results along TDoA based distance estimation results. Distribution of TDoA based results in connected node reduces propagation of erroneous RSSI data among the nodes.

4.2.2 TDoA based indoor localization research

RSSI based location algorithm can provide the approximate location of the object, i.e. vicinity inside a room; therefore, superior distance estimation technique is required to accurately estimate the position. The TDoA technique was introduced as popular localization techniques for airplanes in Long Range Navigation (LORAN-C), long before the introduction of GPS[92]. The system provided location using time difference between the receptions of two low frequency radio signals from a pair of transmitters. The TDoA based distance estimation technique employs static station or nodes with their exact position known by the receiver. The TDoA can be calculated using identical signals with known transmission time or two heterogeneous signals transmitted at the same time.

A wireless sensor network can provide ideal infrastructure for indoor positioning system because of small form factor, low power consumption and scalability of nodes. Excel et al. proposed a TDoA based localization approach by only utilizing single signal
i.e. RF signal. This approach proposes an FPGA based wireless physical layer implementation to achieve a time stamping accuracy in sub nanosecond range. The approach utilizes two timed signals of the same type with known transmission interval. The distance estimations are generated from the time difference of arrival and speed of the signal[93]. This approach faces challenges in implementation on wireless sensor network motes due to the requirement of highly synchronized clock and time stamping on motes.

The interference field created from linear frequency modulation (LFM) waves, simultaneously emitted from two anchor nodes, can be used to estimate TDoA using frequency measurements of RSSI signals [94]. The TDoA is measured at each anchor node to estimate the distance to determine the position. Although this approach only requires RF signals from transceivers and does not require time synchronization, the range estimation accuracy achieved from this approach is around one meter and not appropriate for applications involving tracking of indoor objects such as robots, humans, etc.

A hybrid algorithm consisting of genetic algorithm and quasi-Newton algorithm can increase the stability, localization rate and precision in wireless sensor network [95]. The method developed in this research, deployed group searching characteristics of genetic algorithm and local strong searching technique of the quasi-Newton algorithm. The algorithm improves the results in the presence of increased noise variance although fails to improve results in traditional localization cases and also does not deal with LOS problem.
Various researchers compared efficiency and accuracy of TDoA based location algorithms with RSSI and other types of location algorithms. The ultimate conclusion demonstrated that TDoA based methods are superior in terms of accuracy of the localization and stability in the presence of interference or noise [96][97].

The TDoA can also be achieved by utilizing two separate signals with large difference in propagation velocity. Due to the large difference in their velocity, these signals (transmitted at the same time) are detected by the receiver at different instances of time. The difference between the time of arrival of these signals can be used to calculate the distance between the transmitter and the receiver[98]. The Cricket location system introduced by MIT utilizes RF signal and ultrasonic signals to calculate TDoA measurements. Due to the large difference in the velocities of the RF and the ultrasonic signal, the distance can be estimated by multiplying the TDoA and the velocity of the ultrasonic signal at the room temperature.

The RF and ultrasonic signal based TDoA approach using the Cricket location system has been used for the indoor location system in this research. The Cricket location system faces limitations due to its dependence on LOS communication. The research proposes a unique approach to overcome this limitation and provide robust and accurate position information.

**4.2.3 Why wireless sensor network?**

The exponential growth in processing power of microcontrollers and wireless communication technologies has enabled the creation of small wireless nodes capable of sensing surrounding environment with minimal usage of power. The wireless sensor
network is a network of spatially distributed wireless nodes, working autonomously. As mentioned in the previous section, the wireless sensor networks had been successfully utilized for TDoA based indoor localization research[93][95]. Although wireless sensor networks can be used for localization application using TDoA, their main purpose is to monitor physical or environmental conditions. Due to their sensing capabilities the wireless sensor network provides a strategic advantage for any cyber-physical system compared to other indoor positioning platforms. The wireless sensor nodes are equipped with antenna to communicate with a centralized data aggregation system or they can distribute data independently. Modern wireless sensor nodes are also equipped with modules to interact with the Internet, that can assist in the development of full fledge cyber-physical systems, described in chapter 3.

The WSN based indoor positioning system (IPS) has been selected for the dissertation research due to its mobility, low power consumption, autonomous operations, scalability to a large scale deployment, small form factor, etc. In the WSN terminology, an independent node is also called a mote. Although not all wireless sensor nodes provide functional components to implement TDoA based localization schemes due to the availability of only one wireless signal source, the Cricket motes are being used in this research to provide Indoor position information because of their capability of providing two different signal sources i.e. ultrasonic and radio signal. Following section briefly describes the architecture of the Cricket motes originally introduced at MIT.
4.3 The Cricket motes

4.3.1 Introduction

The Cricket motes were developed by MIT Computer Science and Artificial Intelligent Laboratory with the goals of providing ubiquitous and sensor-based computing. The original Cricket indoor position system consisted of the cricket motes and software application programming interface (API) to provide crisp position information. The Cricket motes can be divided into two categories: (1) Beacons and (2) Listeners. The role of a Cricket can be easily altered by a minor software change.

- **Beacons**: Cricket motes used as stationary motes with known geographical location are called the beacons. Beacons work as pseudo-satellites and periodically broadcast signals with their location and additional information such as id, local temperature, etc. Beacons are mounted at fixed locations such as ceiling or on any static objects.

- **Listeners**: The motes mounted on the mobile devices, being tracked to determine its location information, are known as Listeners. They receive broadcast signals from the reachable beacons within the workspace to calculate their locations.

4.3.2 Cricket motes - hardware architecture

Figure 4.3 shows the basic Cricket motes with hardware components. The complete Cricket hardware architecture can be separated in modules as described below.
• **Processing Module:** Cricket mote deploys an ATMEL Atmega 128L microcontroller operating at 7.3728 MHz in active mode[99]. The microcontroller is an 8-bit processor with 8 kB of RAM, 128 kB of FLASH ROM and 4 kB of EEPROM and can be powered by battery socket or external power supply.

![Figure 4.3: Hardware architecture of Cricket motes[100].](image)

- **Communication Module:** Cricket mote provides two types of wireless communication techniques: RF and ultrasonic. It uses a chipcon CC1000 RF transceiver configured at 433 MHz[101] and a US transmitter and receiver pair working at 40 KHz frequency with a range of 10 meters.

- **External Interface Module:** The main purpose of the 51 pin external interface connector on the cricket mote is to provide I/O expansion. The I/O expansion connector is mainly used to download firmware into the cricket mote. The
Cricket also deploys RS-232 serial connector, which provides an important interface with the host computer. The serial connector is mainly used, in Listener type of motes, to provide collected data from beacons to the host computer.

- **Onboard Sensors:** Cricket contains an onboard temperature sensor, useful in calculating the speed of the ultrasonic signal since the speed of sound is proportional to variations in local temperature. It is also equipped with an 8-byte hardware ID, similar to Ethernet MAC address, to uniquely identify every cricket mote.

### 4.3.3 Cricket motes - software architecture

Figure 4.4 describes the block diagram of the software architecture of the Cricket indoor location system (CILS). A generic block diagram of the CILS consists of four layers: mote (hardware) layer, physical layer, interface layer, processor layer and application layer. The mote layer software (firmware) is targeted for the cricket mote hardware while all other layer applications are hosted on the host computer. Applications associated with software layers can be described as:
- **Mote layer (Cricket firmware):** Cricket firmware is developed in TinyOs using nesC programming language. TinyOs is an event driven and component-based operating system developed at UC Berkeley with Intel Research. It does not include kernel and multithreading to optimize memory limitations and improve power consumption. nesC is an extension of C programming language which employs the concept of “components” and these components are “wired”
together to form whole program. Identical firmware is used for programming both beacon and listener while the role can be changed with a simple command from the serial interface.

- **Interface layer (CricketD):** CricketD is a serial application developed in C to provide an interface between RS 232 serial port of the listener mote and the serial port of the host computer. CricketD binds the serial port to TCP port 2947. The TCP port can be accessed via a network based application for data logging or can be used by CricketDaemon API for further processing.

- **Processor layer (CricketDaemon):** CricketDaemon collects low raw sensor data from CricketD, which includes estimated distance, mote ID, time of flight, local temperature, etc. CricketDaemon utilizes this data to estimate space and position of the listener mote. CricketDaemon broadcasts processed space and position data on TCP port 5001 by default. To calculate position, CricketDaemon requires a configuration file with known position of all beacons being used. CricketDaemon is developed in JAVA programming language.

- **Application layer (Clientlib API):** Clientlib Java library uses callbacks to feed position information to the application. A sample Java application can connect to the ServerBroker object to access the space and position information. The default object can connect to the CricketDaemon running on the localhost via port 5001[102].
4.4 Traditional TDoA approach in CILS

The traditional TDoA based localization approach uses the estimate of distance to calculate the actual position of the object. The algorithm collects the distances from the beacon nodes to the listener node and implements lateration based position estimation. The distance estimation and position estimation techniques are explained in the following sections in detail.

4.4.1 Distance estimation

Cricket motes are capable of estimating distance with 2 centimeter accuracy for a maximum range of 10 meters [100]. Since the speed of the ultrasonic signals vary with temperature, a built in temperature sensor is used to accurately estimate the speed of sound and consequently the speed of the ultrasound signal. Figure 4.5 graphically demonstrates single instance of TDoA based distance estimation between beacon and listener.

The distance estimation in the CILS starts as the beacon motes first transmit a RF signal with a message that contains beacon ID, space ID, coordinates of the beacon and the measured ambient temperature. The beacon also transmits a narrow ultrasonic pulse at the beginning of the RF message, but only the RF signal contains any identifying information. The listener mote mounted on the object receives RF signal first because the speed of RF signal is much greater than the speed of the ultrasonic signal. After receiving the RF signal at time \( T_{rf} \), the listener mote activates the ultrasonic receiver and a timer. It then receives the ultrasonic pulse at time \( T_{us} \), stops the timer, and calculates
the time difference of arrival $\Delta T = T_{us} - T_{rf}$. The distance $d$ is then calculated using equation (4.2),

$$\Delta T = \frac{d}{V_{us}} - \frac{d}{V_{rf}}$$

(4.1)

$$\therefore d = \frac{\Delta T (V_{us}V_{rf})}{(V_{rf} - V_{us})}$$

(4.2)

Figure 4.5: TDoA assisted distance estimation.

The velocity of the RF signal is approximately $3 \times 10^8$ m/s while the velocity of the ultrasonic signal depends upon the temperature and humidity, which is 344 m/s at
standard conditions. Since $V_{rf}$ is much larger than $V_{us}$ at all working temperatures, equation (4.2) can be rewritten as [103],

$$d = \frac{\Delta T (V_{us} V_{rf})}{V_{rf}}$$

(4.3)

where, $V_{rf} \approx V_{rf} - V_{us}$, therefore,

$$\therefore d = \Delta T \cdot V_{us}$$

(4.4)

### 4.4.2 Position estimation

The estimation of the position, for beacons and listeners that have line-of-sight (LOS), is carried out by combining these steps: trilateration or multilateration, least squares minimization (LSM), Kalman filter, and outlier rejection.

Figure 4.6 illustrates the trilateration using three beacon motes and a listener mote. For a system with three beacon motes in the $z = 0$ plane, equation (4.5) is used to find the $x$, $y$, and $z$-position of the listener using trilateration.

$$(x - x_i)^2 - (x - x_i)^2 + z^2 = v^2 t_i^2 = d_i^2, 1 \leq i \leq 3$$

(4.5)

where, $v$ is the speed of sound, $t_i$ is the time taken from the $i^{th}$ beacon to the listener, and $(x_i, y_i)$ is the known position of beacon $i$.  

93
After eliminating $z^2$ by subtracting the three equations (Equation (4.5) for different $i$ values) from each other, the resulting equations can be solved for the unknown position $(x, y)$ of the object with respect to a beacon. For a system with more than 3 beacons motes, the position of the listener can be found more accurately using least square since there are more equations than unknowns[104].

Figure 4.7 shows a basic setup of an IPS having multiple beacons mote mounted on the ceiling and a listener mote on floor level. In the case of multiple beacon motes, the system can have compound numbers of trilateration combinations for beacon motes. This phenomenon can affect the efficiency of the system in either way by providing better average position or one faulty beacon can bring down the average value of the position estimation. In general application it is necessary to use more than three beacons for full room coverage.
The LSM estimates position by minimizing the sum of the squares of the error with respect to each distance sample. A Kalman filter based approach has been integrated to mitigate noise and uncertainty associated with the position data. The listener keeps track of its previous position and velocity to estimate the most probable new position when it receives a new distance sample. The filter can later be used to fuse data from an inertial measurement unit (IMU) and other sensors with information received from the motes. Outlier rejection is used to remove erroneous data[100].
4.2.3 Need for an improved localization system

Although the traditional algorithm provides good position estimation accuracy, it lacks robustness due to its dependence on LOS communication. The presence of acoustic noise disrupts the ultrasonic signal resulting in erroneous distances. The propagation pattern of the ultrasonic pulse also requires the listener to be pointed in the general direction of the beacons. The proposed algorithm is designed to overcome these problems and continuously supply the distances to the localization algorithm.

Figure 4.8 shows the coverage area of the ultrasonic signal with distance estimation error. The listener outside of the optimal coverage area can receive faulty distance readings. The proposed algorithm implements RF resources to overcome the faulty distance results obtained from these motes.

![Figure 4.8: Distance estimation error with respect to angle of ultrasonic transmitter and receiver for different distances[100].](image)
4.5 Proposed fusion based algorithm

The proposed algorithm assumes the measured distance between the beacons and the TDoA measured distance as truth data. The algorithm collects the RSSI for the beacon-beacon, beacon-listener communication and employs the truth data for the training and estimation of the environment factor. The trained factor is further used to estimate the distance in the absence of TDoA based measurements.

4.5.1 RSSI data training phase

In the traditional CILS, individual beacons sequentially send their RF and ultrasonic signal to the listener, while the remaining beacons are in sleeping mode. The algorithm proposes to have all non-transmitting beacons to be listening to the radio signal from the transmitting beacon. In other words, after the transmitting beacon broadcast the RF signal and the acoustic signal, the listener receives and utilizes both signals while the other non-transmitting beacons ignore the acoustic signal and calculate RSSI from the RF signal.
Figure 4.9 demonstrates the first sequence of signal transmission between Cricket motes. During the first sequence, the beacon mote $B_1$ transmits the RF and the US signals, while the listener mote $L$ receives both signals, other beacon motes just receive RF signal. The listener populates a table with received RSSI and TDoA based distance information and other beacons populate a table with just RSSI information. The information in red color i.e. $R_{12}$, $R_{13}$, $R_{14}$ and $R_{1L}$ are the RSSI values measured from RF signals from the current transmission sequence.
Figure 4.10 explains second sequence of signal transmission. In this case, beacon $B_2$ transmits RF and the US signals where the RF signal also includes the RSSI values received in previous transmission sequence. As described in the first sequence, the listener and the rest of the beacons update their tables with RSSI and TDoA based distance information. They also update their table with RSSI information received by the beacon $B_2$ in the first sequence. As the beacons are static and their positions are fixed, the RSSI information measured between the beacons should remain constant for given scenario. Figure 4.10 shows (in purple color) that the listener and other beacons have updated value of $R_{12}$ in their tables.

Figure 4.11 shows fourth sequence of signal transmission, where the listener and the beacons have received values of $R_{14}$, $R_{24}$ and $R_{34}$ from the RSSI measurements.
Figure 4.11: RSSI and TDoA updates from beacon $B_4$.

Figure 4.12 explains the second cycle of signal transmission, where other beacons and the listener update their remaining slots of the tables from updated RSSI values. It should be noted that during all previous sequences, the listener is measuring TDoA based distances while also updating RSSI value from the current transmitting beacon to the listener. As mentioned earlier, due to the fixed position of the beacons, the RSSI value from the beacon $B_1$ to the beacon $B_2$ and from beacon $B_2$ to beacon $B_1$ should be same. Explicitly, we can define the relation between RSSI value as, $R_{ij} = R_{ji}$, where $i,j=1,2,3,4$. 
Figure 4.12: RSSI and TDoA updates from beacon $B_1$ for the second cycle.

Figure 4.13: RSSI and TDoA updates from beacon $B_3$ complete training table.
Figure 4.13 shows that during third sequence of the second cycle, all beacons will have value of corresponding RSSI value in their tables. The algorithm proposed requires a large number of cycles to complete before advancing to the distance estimation phase from RSSI results. The training phase updates and averages the RSSI values between each beacon before the second phase. The training algorithm continuously performs RSSI value update even after the beginning of the position estimation phase, to detect changes in environmental loss factor.

After the completion of initial RSSI training phase, both RSSI training phase and distance estimation phase run in parallel. This configuration is required for purposes such as variance in environmental loss factor, difficulty to obtain TDoA results due to LOS problem, variation in signal propagation model, etc.

4.5.2 Distance estimation from fusion of RSSI and TDoA data

In the simulation, the RSSI value is being calculated from transmitted and received powers of the signal at the receiving end. The ratio of received power versus transmitted power as a function of distance is given by the Friis free space equation (4.6) as follow [105],

\[
P_r(d) = \frac{G_t G_r \lambda^2 P_t}{(4 \pi)^2 d^2 L}
\]  

(4.6)

where, \( P_r \) is the received power, \( P_t \) is the transmitted power, \( G_t \) is the gain of transmitted antenna, \( G_r \) is the gain of receiver antenna, \( L \) is the system loss factor and \( \lambda \) is the wavelength of the transmitted signal in meters. The receiver and transmitter
antenna gains are constant for a fixed environment. The transmitted power $P_t$ is constant for the beacon motes and is fixed to $10^{-3}$ W. Since, only the received power $P_r$ varies according to distance, distance $\hat{d}$ can be obtained from received power $P_r$ from equation (4.8) as,

$$\hat{d}^2 = \frac{G_t G_r A^2 P_t}{(4\pi)^2 P_r(d) L}$$

(4.7)

$$\hat{d}^2 = \left(\frac{G_t G_r A^2 P_t}{(4\pi)^2 L}\right) \frac{1}{P_r(d)}$$

(4.8)

$$\hat{d}^2 = \frac{A}{P_r(d)}$$

where, $A = \left(\frac{G_t G_r A^2 P_t}{(4\pi)^2 L}\right)$, is the system and environment loss factors combined with all constants. Therefore, the distance $\hat{d}$ can be obtained via loss factor and received power as,

$$\hat{d} = \sqrt{\frac{A}{P_r(d)}}$$

(4.9)

In traditional RSSI based algorithms, factor $A$ in equation (4.9) is assumed to be constant for the distance estimation process while in the real world scenarios the loss factor constantly changes according the environmental factors. The algorithm proposes a method to utilize the RSSI values obtained in the training phase to calculate and
update the loss factor $\mathcal{A}$. During the training phase, along with the collected RSSI values, the reference distance were also obtained from the background knowledge containing static location of the beacons. With the actual distance and the known $P_r$ values in term of RSSI, the new equation for the estimated factor $\mathcal{A}$ is given by,

$$
\hat{A} = \sum_{i=1}^{N} \frac{d_i^2(P_r)_i}{N}
$$

(4.10)

where, $N$ represents the number of data points used for running average. The proposed algorithm uses the TDoA measurements as the primary distance estimation method as explained in previous sections since they are not as easily affected by environmental factors the way RSSI measurements are affected. After extensive training, an estimation of the factor $\mathcal{A}$ can be used in conjunction with RSSI measurements in the absence of reliable TDoA measurements. In the case of single or multiple missing TDoA measurements, the trained value $\mathcal{A}$ and an RSSI measurements can be used to estimate the distance using the following equation,

$$
\hat{d}_{\text{trained}} = \sqrt{\frac{\mathcal{A}}{P_r}}
$$

(4.11)

The RSSI trained distance can be used to replace the TDoA based distances (equation (4.5)) for localization. In the event of acoustic noise in the environment disabling the TDoA communication altogether, the proposed algorithm can use the trained value of $\mathcal{A}$ and the RSSI to estimate the distances until the TDoA measurements are available again.
4.5.3 Position estimation

In this approach, similar to any distance based localization technique, obtained distance estimation results are used to calculate the location. The trilateration technique is similar to the one described in section 4.4.2. Section 4.6 describes simulation results obtained from the proposed trilateration algorithm with least mean square (LMS) error on the estimated position results. In application requiring navigation or tracking of a mobile robot or a human, the trilateration technique alone cannot provide efficient results. In these cases, integration of Kalman filter and simultaneous localization and mapping (SLAM) with the current positioning system can augment the efficiency of the overall system. The major augmentations required by these applications are in terms of real-time accuracy and higher frequency of position results. The proposed distance estimation algorithm along with the position estimation technique provides accurate results with higher frequency compared to the traditional CILS algorithm.
4.6 Simulation results of proposed algorithm

In this section, the simulation setup and parameters of the proposed positioning algorithm are described. This section also includes localization results in terms of least mean squared (LMS) error and accuracy obtained from the simulation.

4.6.1 Simulation environment

The simulation uses four fixed beacon motes with known positions. Each beacon mote communicates with a listener mote and other motes in a mesh topology when it is their turn to communicate (time division multiplexing). During each communication sequence, they update an RSSI table of measurements from other beacon motes and the listener. The TDoA table is also updated on every communication cycle between the beacon and the listener. The transmission power $P_{tr}$ of each beacon mote is fixed to $10^{-3}$ watts. For simulation purpose, distance estimation error in TDoA is assumed to be linearly proportional to the actual distance. The RSSI values have been generated as described in section 4.2 but with additional random noise added to the received power and thus the error in estimated distance is proportional to the actual distance.

For training purpose, the simulation is setup to take at least 100 RSSI and TDoA measurements to calculate a running average. After buffer of 100 measurements, the stack gets full and new updates overwrite old RSSI and TDoA values. The trilateration algorithm, explained in Section 4.4.2, is used as preferred localization algorithm on completion of distance estimation after every communication cycle. The Monte Carlo simulations are performed for 100 evaluation cycle keeping listener position stationary.
in 3D space. The LMS error of the performed localization algorithms for each simulation instances is obtained for performance evaluation.

### 4.6.2 Simulation results

In the simulations, three distance estimation schemes TDoA, \textit{fixed A}, and \textit{trained} $\hat{A}$ are evaluated for performance comparison. Figure 4.14 shows position estimation of the listener in 3D space for one instance of the simulation.

![Figure 4.14: Position results for a single instance of localization in 3D space.](image)

Figure 4.15 illustrate LMS error of the estimation and the actual positions for 100 monte carlo simulations. Due to linearity used in TDoA scheme, LMS error is constant for all the simulations for the TDoA. The simulations demonstrate superior localization results of the proposed algorithm on the \textit{fixed A} approach, which represents traditional
RSSI based approach with training. The results also clearly display accurate performance of the proposed algorithm on TDoA based approach.

Figure 4.15: RMS error in position estimation for 25 Monte Carlo simulations.
4.7 Discussion

This chapter described the need for an accurate indoor localization algorithm for a successful implementation of an indoor cyber-physical system. The proposed fusion based indoor localization algorithm provides sufficiently accurate location results for an indoor object in cases where LOS communication is not possible. Once the locations of the static objects in the environment are known in the Cartesian coordinates, these objects will be modeled in the location ontology, described in chapter 5. The location ontology identifies the objects with semantically annotated names such as fireplace, sofa, stove, etc. Although the proposed localization algorithm provided effective results for a simulation environment, the implementation of the proposed algorithm on actual hardware requires design of completely new software architecture.
5 Optimization of Entity Identification Results using Spatial Information

The chapter presents a novel method for efficient situation identification by utilizing spatial information. Section 5.1 provides an introduction to the framework for location-assisted optimization of entity identification results. Section 5.2 describes methodologies to model raw spatial information in semantic map of indoor objects. Section 5.3 describes indoor object based situation assessment from context awareness results obtained in Chapter 3. Section 5.4 provides evaluation of this framework on a simulated implementation of a situation awareness application.
5.1 Introduction

Semantic web based fuzzy abductive reasoning approach for situational context awareness (Chapter 3) exploits the physical sensor information from the environment and does not use spatial information. Thus, in this case, the explained entities are a function of only physical sensor information from the environment. Now, this physical sensor information is associated with or originated from the physical objects in the environment. For example, the temperature context generated from the fire entity should originate from a physical source in the environment. In majority cases of situation awareness, a causal relationship can be established between the entities and the physical objects present in the environment.

In the previous chapter, we introduced an accurate indoor localization algorithm. In a practice implementation of the proposed algorithm, the system provides raw spatial information in terms of Cartesian coordinates. The system also provides information of the spatial domain from which the current spatial information is being obtained i.e. drawing room, bedroom, kitchen, etc. These types of indoor localization systems are deployed with the purpose of serving a single situation awareness system. They lack a mechanism for semantic annotation of these spatial domains to provide interoperability between multiple indoor environments. A systematic method is required to hierarchically model these spatial domains or structural components with the associated indoor objects.

The locations of the static objects, in an indoor environment, can be obtained from background knowledge. A mapping based approach can identify the objects from
raw spatial information using this background knowledge. In a CPS establishment, multiple inter connected indoor environment provides spatial information to the situation awareness system. A generic mapping based approach fails in these circumstances due to irregularities in the domain knowledge and annotation approaches. A unified approach is required to provide interoperability between these environment in terms of annotating the spatial information and the objects. In this dissertation, these static objects in the environment are referred with semantic term,\textit{PointOfInterests} (POIs).

This dissertation provides a hierarchical semantic map approach for representation of indoor POIs. This approach uses ontology to semantically describe the POIs and translates raw spatial information into these semantic objects identifiers. As this semantic map is represented in Web Ontology Language (OWL), it provides semantic interoperability between systems. This dissertation also provides methods to associate situational entities with the objects using OWL. This association further helps the system in effective identification of the situation from entities identified via situational context awareness framework.

Figure 5.1 displays comprehensive framework for situation identification via spatial information based situation assessment. Indoor location ontology provides semantic mapping between raw spatial information and POIs. It also contains association information between the POIs and the applicable entities for those POIs.
Figure 5.1: System framework for location based situation assessment.
5.2 Indoor location ontology

Figure 5.2 displays a generic indoor environment containing multiple types of rooms and indoor objects. A conceptual representation of the indoor environment is required for its successful utilization in a situation awareness application. This representation requires a semantic way of classification of these indoor objects and their functional properties.

![Diagram of indoor environment with various rooms and objects]

**Figure 5.2: Generic indoor scenario of point of interests.**

Various attempts have been made in the domain of autonomous mobile robot navigation to represent indoor environment for efficient path finding and navigation of the mobile robot. These initial approaches included range based and landmark based approach for semantic classification of the indoor environment in the categories of
rooms and indoor objects[106],[107]. Galindo et al. [108] and Zender et al. [109] presented multi-hierarchical and multi-layer semantic map based representation utilizing spatial and semantic information. These approaches used laser and vision based techniques to locate the indoor objects in the environment, while this dissertation focuses on absolute spatial information, achieved from the localization system. Wang & Chen [110] proposed semantic map based representation of indoor environment utilizing prior knowledge regarding proximity correlation between objects. This dissertation presents a hierarchical map representation of the indoor environment in the form of Web Ontology Language (OWL). This OWL representation also exploits background knowledge containing location of the indoor objects to translate raw spatial information into semantic object annotation.

5.2.1 Object classes

In the semantic map model, the components of the indoor environment are classified in two principal classes: StructuralComponents and PointOfInterest. The StructuralComponents class includes planner objects, while the PointOfInterest class includes static objects and furniture in the indoor environment. The subclasses of the StructuralComponents class include Room and Corridor. The Room class has various types of regional components as subclasses such as DrawingRoom, BedRoom, Kitchen, Office, ConferenceRoom and Gym. The PointOfInterest class includes subclasses such as SofaPOI, TredmillPOI, ChairPOI, BedPOI, FirePlacePOI, etc., to model various indoor objects. Figure 5.3 shows this hierarchical structure via a semantic graph. In OWL, the relationships between various objects are modeled in a triple format,
where, \( T \) is the relationship triple, \( S \) represents subjects, \( O \) represents objects and \( P \) describe predicates or properties between these subjects and objects. In proposed map structure, subclasses (subjects \( S \)) are associated with perspective classes (objects \( O \)) with relationship property \textit{is-a}. Inverse relationship between parent class and their subclass is represented by the \textit{has-subclass} property.

\[ T = (S, P, O) \]  

\[ \text{(1)} \]

\hspace{1cm} \text{Figure 5.3: Class hierarchies for indoor components and POIs.} \]
This dissertation provides a conceptual framework for categorization and semantic map representation of indoor objects. The number of subclasses for \textit{StructuralComponent, Room} and \textit{PointOfInterest} are not limited to specified subclasses described in Figure 5.3. Various applications can employ this mapping technique to model other subclasses of the \textit{PointOfInterest} and the \textit{Room} classes.

5.2.2 Spatial association object properties

An indoor environment may contain multiple objects representing identical class e.g. multiple chairs. In semantic web, concept of \textit{individual} is used to create an instance of objects representing the same class. For example, \textit{Office} class characterizes a concept of the office, while for two different office rooms in an indoor environment; two difference individuals are required, \textit{Office-1} and \textit{Office-2}. Both of these individuals inherit properties from their parent class \textit{Office} and the relationships between them are specified by property \textit{has-individual}.

To establish the relationship between the regions of the indoor environment and the objects presence in those regions, the dissertation introduces two object properties, \textit{hasPOI} and \textit{isLocatedIn} as described in Table 5.1.

\textit{Table 5.1: Indoor object properties and their descriptions.}

<table>
<thead>
<tr>
<th>Object property</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>\texttt{hasPOI}</td>
<td>Relate the individuals of subclasses of \textit{Room} class with individuals of subclasses of \textit{PointOfInterest} class.</td>
</tr>
<tr>
<td>\texttt{isLocatedIn}</td>
<td>Relate the individuals of subclasses of \textit{PointOfInterest} class with individuals of subclasses of \textit{Room} class.</td>
</tr>
</tbody>
</table>
The object properties *hasPOI* and *isLocatedIn* can be classified as mutually inverse properties. An individual of *Room* can have multiple objects hence multiple *hasPOI* properties associations while an object can have only single *isLocatedIn* in property. Cases where a static object is located in multiple rooms are obscure and hence are avoided in this dissertation. Figure 5.4 explains *hasPOI* and *isLocatedIn* properties in detail. The *BedRoom-1* is an individual of the *BedRoom* class while the *BedRoom* is a subclass of the *Room* class. *BedRoom* class has multiple individuals *BedRoom-1* and *BedRoom-2*. Two different objects, a bed and a chair, are present in the *Bedroom-1* and they are related to the *BedRoom-1* with multiple *hasPOI* properties. These individuals, *Bed-1* and *Chair-1*, are related with their respective parent class with *has-individual* property.

*Figure 5.4: Relationship among POI individuals and structural individuals.*
This method can be applied to establish the relation between Individual objects, their respective class and the region containing those individuals. In OWL, these relationships are defined as follow,

```
<owl:ObjectProperty rdf:about="#hasPOI">
  <owl:inverseOf rdf:resource="#isLocatedIn"/>
  <rdfs:domain>
    <owl:Restriction>
      <owl:onProperty rdf:resource="#hasPOI"/>
      <owl:someValuesFrom rdf:resource="#PointOfInterest"/>
    </owl:Restriction>
  </rdfs:domain>
</owl:ObjectProperty>

<owl:ObjectProperty rdf:about="#isLocatedIn">
  <owl:inverseOf rdf:resource="#hasPOI"/>
  <rdfs:domain>
    <owl:Restriction>
      <owl:onProperty rdf:resource="#isLocatedIn"/>
      <owl:someValuesFrom rdf:resource="#StructuralComponent"/>
    </owl:Restriction>
  </rdfs:domain>
</owl:ObjectProperty>
```

### 5.2.3 Effective coverage space and datatype properties

The dissertation proposes the concept of effective coverage space to translate the raw spatial information with the appropriate objects. The effective coverage space of the object is defined by the physical area occupied by the object or the operational space of that object in the 3D environment. For example, the effective coverage space of a chair is not limited to the actual space occupied by the chair but also includes the space in which an associated event can take place. In the real world applications, the effective coverage area of an object can have multiple shapes. In this dissertation, the cuboid is considered as default shape to represent every object in the environment. Dissimilar 3D coverage shapes can be converted into cuboid shape with minor loss in accuracy of the object annotation model.
A rule-based approach can locate the objects from raw spatial information by specifying limits on X, Y and Z coordinates of the cuboid. Semantic modeling of these rules in OWL can enable rule-based reasoning and provides interoperability in scenarios where the indoor ontology is used by different applications. The dissertation introduces OWL datatype properties to model the 3-dimensional limit of the cuboid. A methodology to translate the spatial information in the individuals of the class `PointOfInterest` is also provided. Table 5.2 describes proposed datatype properties as follow,

*Table 5.2: Datatype properties and their descriptions regarding effective coverage area.*

<table>
<thead>
<tr>
<th>Datatype property</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>hasXmax</td>
<td>Maximum coverage of the object in X dimension</td>
</tr>
<tr>
<td>hasXmin</td>
<td>Minimum coverage of the object in X dimension</td>
</tr>
<tr>
<td>hasYmax</td>
<td>Maximum coverage of the object in Y dimension</td>
</tr>
<tr>
<td>hasYmin</td>
<td>Minimum coverage of the object in Y dimension</td>
</tr>
<tr>
<td>hasZmax</td>
<td>Maximum coverage of the object in Z dimension</td>
</tr>
<tr>
<td>hasZmin</td>
<td>Minimum coverage of the object in Z dimension</td>
</tr>
<tr>
<td>hasUnit</td>
<td>Unit of the raw spatial information</td>
</tr>
</tbody>
</table>
These datatype properties are only appropriate for cuboid shaped coverage space and assumed to be obtained from the background knowledge regarding the indoor environment. In reference to the origin, these datatype properties should follow $hasXmin \leq hasXmax$, $hasYmin \leq hasYmax$ and $hasZmin \leq hasZmax$ criteria. The indoor objects are required to be described by all appropriate datatype values for the effective utilization of the raw spatial information. Figure 5.5 shows Chair-1 object with its superclass, coverage datatype properties and spatial-association object properties with a graph representation. The Chair-1 is an individual of the class ChairPOI and is located in the DrawingRoom-1, which is an individual of the DrawingRoom class. The $hasXmin$, $hasXmax$, $hasYmin$, $hasYmax$, $hasZmin$ and $hasZmax$ datatype property of Chair-1 carries values 610 cm, 760 cm, 240 cm, 360 cm, 0 cm and 100 cm, respectively,
in reference to the origin located at (0,0,0). The graph displayed in Figure 5.5 can be serialized in RDF represented as following,

```xml
<owl:Class rdf:about="#Room">
  <rdfs:subClassOf rdf:resource="#StructuralComponent"/>
</owl:Class>
<owl:Class rdf:about="#DrawingRoom">
  <rdfs:subClassOf rdf:resource="#Room"/>
</owl:Class>
<owl:NamedIndividual rdf:about="#DrawingRoom-1">
  <rdf:type rdf:resource="#DrawingRoom"/>
  <hasPOI rdf:resource="#Chair-1"/>
  <hasPOI rdf:resource="#Fireplace-1"/>
  <hasPOI rdf:resource="#Sofa-1"/>
</owl:NamedIndividual>
<owl:Class rdf:about="#ChairPOI">
  <rdfs:subClassOf rdf:resource="#PointOfInterest"/>
</owl:Class>
<owl:NamedIndividual rdf:about="#Chair-1">
  <rdf:type rdf:resource="#ChairPOI"/>
  <hasZmin rdf:datatype="&xsd;float">0.0</hasZmin>
  <hasZmax rdf:datatype="&xsd;float">100.0</hasZmax>
  <hasXmax rdf:datatype="&xsd;float">760.0</hasXmax>
  <hasXmin rdf:datatype="&xsd;float">610.0</hasXmin>
  <hasYmin rdf:datatype="&xsd;float">240.0</hasYmin>
  <hasYmax rdf:datatype="&xsd;float">360.0</hasYmax>
  <hasUnit rdf:datatype="&xsd;string">cm</hasUnit>
  <isLocatedIn rdf:resource="#DrawingRoom-1"/>
</owl:NamedIndividual>
```

**5.2.4 Semantic object identification**

The raw spatial coordinates \((x,y,z)\) are translated into the appropriate `PointOfInterest` via the following equation.
IdentifiedPOI

\[\equiv \{\exists inLO: PointOfInterest. \{inLo: hasXmax \geq x}\}\]
\[\land \{\exists inLO: PointOfInterest. \{inLo: hasXmin \leq x\}\}\]
\[\land \{\exists inLO: PointOfInterest. \{inLo: hasYmax \geq y\}\}\]
\[\land \{\exists inLO: PointOfInterest. \{inLo: hasYmin \leq y\}\}\]
\[\land \{\exists inLO: PointOfInterest. \{inLo: hasZmax \geq z\}\}\]
\[\land \{\exists inLO: PointOfInterest. \{inLo: hasZmin \leq z\}\}\]

(5.1)

Equation (5.1) performs conjunction operation on each PointOfInterest satisfying the limitations in datatype properties. The evaluation of this approach is presented in Section 5.4.1 with a practical example.
5.3 Location based situation assessment

Chapter 3 provided candidates for situation comprehension in terms of entities, identified from the environmental context information at various spatial locations in the indoor environment. The dissertation also presented methods to annotate these raw spatial locations in semantic objects in Section 5.2. This section provides the mechanism for efficient situation assessment via exploiting association of these semantic objects with the contextual entities in these steps: (1) modeling *PointOfInterest-Entity* relationships, (2) spatial situation assessment from these relationships and (3) certainty calculation of the assessed situation.

5.3.1 Object properties for relationship between individuals of *PointOfInterest* and *Entity*

The entities cannot be conclusively identified due to lack of sufficient applicable domain knowledge at some spatial locations. For example, a condition such as hypertensive heart disease (*HTHD*) cannot be conclusively identified at the *treadmill* because the physical sensor information may provide increased perspiration and elevated heart rate, which explain the *HTHD* but may be produced from a person exercising. Therefore, in the absence of sufficient background knowledge, the *HTHD* can be now considered as the not-applicable entity at the *treadmill*. Similarly, even though the *fireplace* produces temperature and carbon dioxide context, which can be explained from the *fire* entity, the *fire* cannot be considered as the applicable entity for situation awareness at the *fireplace*. 
The dissertation introduces two objects properties in OWL, \textit{hasApplicableEntity} and \textit{hasNotApplicableEntity}, to model spatial relationship between the \textit{PointOfInterest} and appropriate entities, describe in Table 5.3. These object properties are mutually inverse properties and thus modeling of only one property is required to represent these relationships.

\textit{Table 5.3: Object properties for relationship between POI and entities.}

<table>
<thead>
<tr>
<th>Object property</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>\textit{hasApplicableEntity}</td>
<td>Entities, considered as the preferred candidate for the situation at the \textit{PointOfInterest}.</td>
</tr>
<tr>
<td>\textit{hasNotApplicableEntity}</td>
<td>Entities, not considered as the preferred candidate for the situation at the \textit{PointOfInterest}.</td>
</tr>
</tbody>
</table>

\textit{Figure 5.6: Relationship between POIs and entities for different objects in the DrawingRoom-1.}
Figure 5.6 shows multiple PointOfInterest located in Drawingroom-1, and their associations with appropriate entities via hasApplicableEntity property. The Fireplace-1 object has only DryIce and NormalCondition as the applicable entities, while the Sofa-1 and the Chair-1 can have all entities as candidates for the applicable entities. The relationship graph in Figure 5.6 can be represented in OWL as following,

```
<owl:Class rdf:about="#ChairPOI">
  <rdfs:subClassOf rdf:resource="#PointOfInterest"/>
</owl:Class>
<owl:NamedIndividual rdf:about="#Chair-1">
  <rdf:type rdf:resource="#ChairPOI"/>
  <isLocatedIn rdf:resource="#DrawingRoom-1"/>
  <hasApplicableEntity rdf:resource="#DryIce"/>
  <hasApplicableEntity rdf:resource="#Fire"/>
  <hasApplicableEntity rdf:resource="#HighHeartRate"/>
  <hasApplicableEntity rdf:resource="#NormalCondition"/>
  <hasApplicableEntity rdf:resource="#PresenceOfRoomHeater"/>
</owl:NamedIndividual>
```

5.3.2 Location based entity discrimination

The comparison of applicable entities at the identified PointOfInterest and the entities obtained from the situational context awareness at the same location provides an assessment of the actual situation. The discrimination of entities obtained from physical context in reference to the applicable entities can be performed by conjunction operation in first order logic via the following equation,

\[
\text{Situation} \equiv \{\text{Entity(physicalContext)}\} \sqcap \{\text{applicableEntity(PointOfInterest)}\}
\] (5.2)
5.3.3 Certainty of the assessed situation

Equation 5.2 provided optimized entity identification based on spatial location. The entities obtained from the physical context also contained certainty numbers from the methods describe in Chapter 3. It is necessary to obtain the certainty degree for the identified situation after spatial reasoning for the efficient situation comprehension. Although the certainty number for the applicable and not-applicable entities can have different values according to the application requirements, the dissertation assumes the certainty confidence of the applicable and not-applicable entities as 1 and 0, respectively.

\[
\mu(\exists inLo: hasApplicableEntity(PointOfInterest))) = 1
\]
\[
\mu(\exists inLo: hasNotApplicableEntity(PointOfInterest))) = 0
\]

(5.3)

The certainty of the assessed situation can be achieved via performing fuzzy conjunction operation on each entity obtained from the physical context and applicable entities at the PointOfInterest, as shown in equation (5.4).

\[
\mu(Situation) \equiv \mu(\{situationalEntity(PointOfInterest)\})
\]
\[
\quad \land \mu(\{hasApplicableEntity(PointOfInterest)\})
\]
\[
\equiv \min(\mu_s(PointOfInterest), \mu_L(PointOfInterest))
\]

(5.4)
where, $\mu_s$ is the membership number of entities obtained from the situational context awareness at the $PointOfInterest$ and $\mu_L$ is the membership number of entities applicable at the $PointOfInterest$. 
5.4 Implementation and evaluation

Figure 5.7: Raw spatial coordinates of the indoor objects in the experimental setup.

The evaluation of the proposed location based methodology for optimization of entity identification was performed using an experimental setup described in Figure 5.7. The indoor objects were semantically modeled in the indoor location ontology. The indoor location ontology also contained the associations between the indoor objects and the entities to be determined. The experimental setup included multiple indoor objects and fire entities were simulated at the Fireplace-1 and Chair-1 locations whereas the fire at the Chair-1 was only considered as the actual situation. The raw
environmental context was obtained via mobile sensing platform while the certainty of entities for situational context was obtained via the method described in Chapter 3. Figure displays the indoor objects with their coverage area in Cartesian coordinates and track of the mobile sensing platform. For explanation purpose, the coverage area of the indoor objects was considered as 2-dimensional containing only $X$ and $Y$ coordinates. The raw spatial information of the mobile platform was provided by the wireless sensor based indoor positioning system.

5.4.1 Indoor object identification

The evaluation of semantic object identification and location based situation assessment operation was performed at each point on route of the mobile platform. In this section, two distinct locations are considered for a detailed explanation of these operations. Figure 5.7 shows locations (a) and (b) on the mobile platform path with existing indoor objects in the Drawingroom-1. The spatial information obtained from the indoor position system only contained $X$ and $Y$ coordinates of these locations. As the coverage areas of the indoor objects were modeled in the indoor location ontology, the semantic object identification can be performed through the method described in Section 5.2.4. The process of obtaining $PointOfInterest$ for location (a) is describe through Equation 5.5 as following,
IdentifiedPOI

\[\equiv \{\exists \text{inLO:PointOfInterest.}\{\text{inLo:hasXmax} \geq 190\}\}\]
\[\quad \cap \{\exists \text{inLO:PointOfInterest.}\{\text{inLo:hasXmin} \leq 190\}\}\]
\[\quad \cap \{\exists \text{inLO:PointOfInterest.}\{\text{inLo:hasYmax} \geq 570\}\}\]
\[\quad \cap \{\exists \text{inLO:PointOfInterest.}\{\text{inLo:hasYmin} \leq 570\}\}\]

\[\equiv \{\text{Sofa} - 1, \text{Plat} - 1, \text{Fireplace} - 1\}\]
\[\quad \cap \{\text{Sofa} - 1, \text{Plat} - 1, \text{Fireplace} - 1\}\]
\[\quad \cap \{\text{Fireplace} - 1\}\]
\[\quad \cap \{\text{Sofa} - 1, \text{Plat} - 1, \text{Fireplace} - 1, \text{Chair} - 1\}\]

\[\equiv \{\text{Fireplace} - 1\}\]

similarly, indoor PointOfInterest for location (b) was identified using equation (5.6).

IdentifiedPOI

\[\equiv \{\text{Sofa} - 1, \text{Plat} - 1, \text{Fireplace} - 1, \text{Chair} - 1\}\]
\[\quad \cap \{\text{Chair} - 1\}\]
\[\quad \cap \{\text{Sofa} - 1, \text{Fireplace} - 1, \text{Chair} - 1\}\]
\[\quad \cap \{\text{Sofa} - 1, \text{Plat} - 1, \text{Chair} - 1\}\]

\[\equiv \{\text{Chair} - 1\}\]

(5.6)
Equations 5.5 and 5.6 identified \textit{PointOfInterest} for location \textit{(a)} and \textit{(b)} as the \textit{Fireplace-1} and the \textit{Sofa-1}, respectively. These obtained semantic object identifiers were then converted in the RDF format for these locations with applicable entities at those locations.

\subsection*{5.4.2 Spatial information based situation assessment}

From situation context awareness results obtained from Chapter 3, the \textit{Fire} and the \textit{RoomHeater} entities are identified from raw environmental sensor data for these locations. Location based situation assessment was implemented at these locations using the method described in Section 5.3.2. The applicable entities at \textit{Fireplace-1} are \textit{NormalCondition} and \textit{DryIce}, as described in the indoor location ontology. The situation at location \textit{Fireplace-1} is calculated via first order logic as following,

\begin{align*}
\text{Situation} & \equiv \{\text{Entity(physicalContext)}\} \cap \{\text{applicableEntity}(\text{Fireplace-1})\} \\
& \equiv \{\text{Fire, RoomHeater}\} \cap \{\text{NormalCondition, DryIce}\} \\
& \equiv \emptyset
\end{align*}

(5.7)

Equation 5.7 shows that the evaluated situation at the location \textit{Fireplace-1} is an empty set. Although situation context awareness identified \textit{Fire} and \textit{RoomHeater} entities at the \textit{Fireplace-1}, the optimized results, through spatial entity relationship, contained null situation. In other words, no situation was assessed at the \textit{Fireplace-1}. Similarly, the optimized situation result at the location \textit{Chair-1} was calculated using equation (5.8).
These results provided the Fire and the RoomHeater entities as possible situation candidates for the location Chair-1. The certainty degree of these entities were calculated using method describe in Section 5.3.2 as follow,

\[
\mu(Situation) \equiv (\mu_s(Fire), \mu_s(RoomHeater), \mu_s(NormalCondition), \mu_s(DryIce)) \\
\land (\mu_L(Fire), \mu_L(RoomHeater), \mu_L(NormalCondition), \mu_L(DryIce)) \\
\equiv (\min(\mu_s(Fire), \mu_L(Fire)), \min(\mu_s(RoomHeater), \mu_L(RoomHeater))) \\
\equiv (\mu(Fire) = 0.9, \mu(RoomHeater) = 0.1)
\]

(5.9)

Equation 5.9 provided certainty degree of the Fire and the RoomHeater entities as 0.9 and 0.1, respectively. At the location Chair-1, the situation was concluded as the Fire due high certainty degree compared to the RoomHeater.
5.4.3 Evaluation for complete mobile robot route

As described in the beginning, the semantic object identification and spatial situation assessment were performed at each point on the mobile robot path. The goal of this experiment was to identify and calculate certainty of the simulated fire entity at those points. Figure 5.8 compares the obtained results with the background knowledge of the simulated fire on the mobile robot path. The implementation of the proposed methodology provided 96%, 94% and 92% efficiency in the situation assessment for the certainty cut off of 0.75, 0.5 and 0.25, respectively. Evaluation of location aided fuzzy abductive reasoning in comparison to crisp and fuzzy abductive reasoning approaches to detect actual fire situation at the Chair-1 object is displayed in Table 5.4.

Table 5.4: Evaluation of crisp and fuzzy abductive reasoning approaches for detecting actual indoor fire situation.

<table>
<thead>
<tr>
<th>Reasoning approach</th>
<th>Precision</th>
<th>Recall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Location aided Fuzzy abductive reasoning</td>
<td>100%</td>
<td>88.89 %</td>
</tr>
<tr>
<td>Fuzzy abductive reasoning</td>
<td>100 %</td>
<td>50 %</td>
</tr>
<tr>
<td>Crisp abductive reasoning</td>
<td>87.5 %</td>
<td>43.75 %</td>
</tr>
</tbody>
</table>

Figure 5.9 compares the spatial situation assessment results with the crisp and fuzzy abductive reasoning approach without location assistance.
Figure 5.8: Comparison of the actual fire situation at Chair-1 and the estimated fire situation at 0.75, 0.5 and 0.25 certainty number.

Figure 5.9: Evaluation of location aided fuzzy entity identification.
6 The Situation Awareness Framework and Application Cases

This chapter presents comprehensive situation awareness framework for the CPS with respect to approaches described in previous chapters. The chapter also provides simulation results for an application scenario, using the proposed framework, and the implementation guidelines for numerous other application cases. Section 6.1 describes the system level and the semantic modeling frameworks with a detailed description of internal components. Section 6.2 demonstrates an experimental scenario involving fire and explains the significance of the framework components in reference to the scenario. Section 6.3 provides outlines of the various known CPS application cases for the domains of patient monitoring, indoor disaster management and weathercasting.
6.1 The Situation awareness framework

In previous chapters, a methodology to handle challenges associated with the cyber-physical systems such as uncertainty, interoperability, situational context awareness and location awareness was presented. The semantic abstraction approach aided by fuzzy abductive reasoning identified entities from raw physical context information. Indoor objects and their relationship with contextual entities provided efficient situation assessment. The semantic web based information modeling and domain knowledge helped in achieving interoperability between various CPS implementations. This section provides a systematic comprehensive framework, incorporating these approaches, to achieve efficient situation awareness. The comprehensive framework is presented in two distinct models, the system level framework and the semantic modeling framework.

6.1.1 System level framework

Figure 6.1 illustrates the comprehensive system level framework that consists of functional concepts and components of the proposed situation awareness and the entity identification system. These components are classified into two key sections: physical level components and cyber level components.
The physical level components interact with the real world environment to aggregate raw sensory context while the cyber level components consist of reasoning mechanism and provide situational outcome from this raw sensor information. The reasoning mechanism is implemented on a mobile platform. In scenarios where multiple mobile platforms are utilized, the reasoning mechanism can be employed on a remote system using Internet. The physical and cyber level components are described below.

**Physical level components:**

1. **Environment sensors:**

   This component consists of sensors interacting with physical events and collect physical contextual data. These sensors can be part of a mobile sensing platform or can exist as a static sensor unit. Environment monitoring sensor and personal body area sensors are normally classified in this category. Temperature sensor, Carbon Dioxide sensor, humidity sensor etc. are examples of physical environmental sensor while heart
rate monitor, galvanic skin response sensor, blood pressure sensor etc. are examples of body area monitoring sensors. The aggregated sensor data is in continuous real-time format and sent to reasoning mechanism for further analysis.

(2) Indoor positioning system:

The positioning system estimates the raw spatial information of the mobile sensor platform in Cartesian coordinate system. This dissertation utilizes wireless sensor network based indoor positioning system for accurate and absolute localization. Various vision and inertial measurement unit based approaches can be used in place of sensor network based approach with the assumption that they provide accurate and absolute location in Cartesian coordinate system.

**Cyber level components:**

(1) Domain knowledge:

Ontologies are used as a standard to represent the domain knowledge and to assist the reasoning process. The domain knowledge consists of application specific entities and their relationship with qualities and raw sensor information. The domain knowledge also contains the spatial information regarding the indoor objects and their associations with the explicit entities.
(2) Situational context awareness:

This component exploits the domain knowledge to classify the raw sensor context in qualities (low-level abstractions) such as high temperature, low carbon dioxide, etc. Entities (high-level abstractions) such as fire, dry-ice, etc., present in the environment, explain these qualities by implementing fuzzy abductive reasoning approach. These entities are used as candidates for the assessment of applicable situation further in the framework.

(3) Location awareness:

The domain knowledge translates raw spatial information obtained from the indoor positioning systems into semantic object identifier. The entities from the contextual situation awareness and the applicable entities at the identified objects are compared to determine the actual situation.

6.1.2 Semantic modeling framework

Semantic web based annotation and reasoning approaches assist in achieving interoperability for the cyber-physical systems. These approaches also help in modeling and deployment of complex reasoning rules and relationship between components. Figure 6.2 displays annotated data at various stages of the framework and ontologies used for annotation and reasoning. The Semantic Sensor Network (SSN) ontology assists in encoding raw sensor data into Resource Description Framework (RDF) format[111][76]. As SSN is a standard developed by W3C, this RDF data can be exploited by multiple CPSs. During each step of the reasoning process, the data maintains its RDF
format while the annotation standard gets altered with respect to the component and the applied ontology.

The raw sensor data, annotated using SSN, is further decoded into qualities using the domain ontology. The domain ontology contains domain specific description of the context sources and rules to obtain low-level fuzzy abstractions from raw sensor information. For instance, the domain ontology defines and models low-level abstractions such as high temperature, low temperature, high heart rate, etc. with their ranges and properties. Entities are obtained from these low-level abstractions using the reasoning ontology. The reasoning ontology contains the fuzzy abductive reasoning rules specifying the relationship between the qualities and the entities. These entities, obtained from the situational context awareness model, now represent the events in the environment with calculated certainty number.

The spatial information in the Cartesian coordinate system of the mobile platform, obtained from the indoor positioning system, is translated into semantic object identifier using the indoor location ontology. The indoor location ontology contains the information of the effective cuboid coverage space of an indoor object and utilizes it to identify the indoor objects from the raw location of the mobile platform. The indoor location ontology also provides the association between applicable entities at the identified object and compares them with the entities obtained from contextual situation awareness model to comprehend the situation.
Figure 6.2: Semantic modeling framework.
6.2 Application case: simulated indoor fire

This section details the experimental evaluation of the proposed framework in a laboratory simulation environment along with describing the significance of each framework component from the results obtained. The motivation behind the experiment is to efficiently detect fire situation from physical context and spatial information.

6.2.1 Simulation setup

The experimental setup had two isolated focus entities: a fire at a fireplace and a chair of fire. The fire entities were simulated using candles and were spatially isolated in the laboratory. The environment also contained context sources such as a room heater, people etc. effecting the contexts information generated from those fire. A mobile sensing platform, equipped with temperature and carbon dioxide sensors, was used to acquire physical context information from the entities. The mobile sensing platform also contained the reasoning mechanism for entity identification. The experimental setup was assisted by an indoor positioning system using wireless sensor network. A listener mote was mounted on the mobile platform to receive accurate spatial information. The domain knowledge involving entity relationship and reasoning rules was obtained from a domain expert.
6.2.2 Situational context and spatial information acquisition

During the experiment, the mobile sensing platform navigated through the effective cuboid coverage space of the indoor objects to acquire the context information. Figure 6.4 shows the path of the mobile platform and the effective coverage area of the fireplace and the chair. As the real fireplace and chair were not used for this experiment, the effective coverage areas were assumed and modeled in ontology. The carbon dioxide and temperature context were observed via the mobile platform and encoded in the RDF format using SSN ontology. Simultaneously, for the same points, the mobile platform received raw spatial information from the indoor positioning system.
Figure 6.4: Raw physical sensor information from context source.

Figure 6.5 shows two points in the coverage space of the fireplace and the chair, where the raw spatial information and physical context information were collected by the mobile platform. During its route through the coverage areas, the mobile platform obtained spatial and context information from numerous points. Although analysis was performed at each location on the path, two distinct locations have been selected to explain the analysis in detail. The raw spatial and physical values were converted in RDF format using SSN ontology to be further used by reasoning components.
6.2.3 Fuzzy abductive reasoning with uncertainty modeling

The fire entity explained high temperature and high carbon dioxide qualities. These qualities were affected by other context sources present in the environment such as a room heater and people. To cope with this uncertainty, the temperature and carbon dioxide context were divided into fuzzy abstractions of high temperature, low temperature and high carbon dioxide, low carbon dioxide, respectively. The reasoning ontology contained the domain knowledge base explaining the relationship between the entities and the qualities in OWL. The implementation of fuzzy abductive reasoning using this ontology provided certainty of the recognized entities. For the location \(a\), certainty of fire and heater were 0.8 and 0.2, respectively, while at the location \(b\) these certainties were 0.9 and 0.1, respectively. Figure 6.6 shows certainty degree of the fire entity for these locations obtained by the mobile platform. In summary, the situational
context awareness component of the framework encoded the raw context information and identified entities with certainty numbers for the experimental setup.

![Figure 6.6: Identified entities using fuzzy abductive reasoning.](image)

![Figure 6.7: Translation of raw spatial information to semantic POI identifiers.](image)
6.2.4 Semantic object identification

The indoor location ontology contained the model of the effective cuboid coverage space of the context sources in the Cartesian coordinates. The model included limitations of the coverage space in X, Y and Z directions. The raw spatial information of the location (a) and (b) were converted into semantic object identifiers *Fireplace* and *Chair*, respectively, using semantic reasoning and the indoor location ontology. Figure 6.7 shows these points with their semantic annotation and associated entities along with the certainty confidence. In summary, this component provides affiliation of indoor object with identified situational context results.

6.2.5 Location based entity discrimination

*Figure 6.8: Location based entity discrimination.*
The indoor location ontology also contained the relationships between indoor objects and applicable entities for those objects. The fireplace, while in use, produces high temperature and carbon dioxide contexts. Hence, the entities such as a fire and the presence of a room heater cannot be considered as an actual fire situation in this case. Therefore, the fire and the presence of room heater were considered as not applicable entities at the fireplace and were modeled in the indoor location ontology. The fire situation with high certainty of 0.9 was calculated at the chair using spatial entity discrimination, described in chapter 5.

In summary, the significance of each component of the proposed framework in the situation comprehension process for a CPS is described in this section. Although, these components provide a novel approach for the entity identification process and can be used independently, the implantation of the comprehensive framework provides efficient situation assessment results.
6.3 Proposed application scenarios

A successful experimental implementation of the proposed situation awareness framework on an indoor fire scenario was presented Section 6.2. The experiment contained abstraction and reasoning rules consisting of two context sources, four qualities and a single entity. Simulation of an indoor fire in a controlled laboratory environment is a challenging task, which was the primary reason for having a small number of qualities involved in the experiment. Implementation of the proposed framework to a real world application requires extensive background knowledge from domain experts. This domain knowledge, which provides the basis for reasoning and abstractions rules, is subjected to change with different applications.

The proposed framework can be easily ported to other CPS application domains in the presence of proper domain knowledge. This section proposes enhancements over known application cases in various domains with efficient uncertainty handling and effective use of spatial context.

6.3.1 Indoor patient monitoring system

In recent years, various technological advancements have enabled the development of inexpensive sensors to aid the body area monitoring systems. The remote patient monitoring has become a popular research field for the healthcare domain. Researchers have tried to leverage this sensor revolution by creating advance application for the heart diseases[61], [112]. These researchers utilize a combination of questionnaire context and physical sensor context, acquired from the smart phone and body area monitoring sensors, to evaluate health of a patient. Suh et al. employed an
approach which utilizes crisp cutoff limits in raw sensor data to infer qualities such as high heart rate, weight gain, etc[112]. Perera et al. presented data driven knowledge acquisition method assisted by cardio ontology and abductive reasoning framework[61]. These approaches can be extended by introducing the use of spatial information and uncertainty modeling proposed in this dissertation.

Figure 6.9 displays subset of a comprehensive remote patient monitoring system to explain effective utilization of the proposed framework. The patient is considered as a mobile sensing unit mounted with a body area sensor network, which includes a heart rate monitor, a galvanic skin response sensor, a location sensors and a local temperature sensor. The galvanic skin response sensor provides perspiration data by measuring electric conduction of the skin while the temperature sensor measures environment temperature surrounding the patient. The room contains indoor objects such as a refrigerator, a stove, a treadmill and a bed. A static temperature sensor is mounted at the stove to provide environmental context at the stove. An operator, located remotely, is monitoring the situation and the goal of the framework is to present efficient situation to the operator to take proper actions.
Figure 6.9: An indoor patient monitoring scenario.

Figure 6.10 shows modeling of entity detection rules in a graph format with fuzzy quality abstractions and context sources as quality-type. The primary health related entity to be identified is hypertensive heart disease, while the secondary entities are stove on or off and hot or cold room condition. The definitions of hot and cold room environment are a function of the patient preferences and present season. This distinction can be achieved by introducing fuzzy abstractions for the temperature qualities. Similarly elevated and regular heart rate qualities are dependent upon medical history, age, sex etc. of the patient and represented as fuzzy abstractions. The Hypertensive Heart Disease (HTHD) explains elevated heart rate and increased perspiration qualities and can be stated as following,

\[ \text{Explanation}(HTHD) = \{ \exists \text{inheresIn.\{elevatedHeartRate\}} \} \cap \{ \exists \text{inheresIn.\{increasedPerspiration\}} \} \]  \hspace{1cm} (6.1)
Similarly, the high and low temperature at stove can be explained from the stove on or off entities. The reasoning rules displayed in Figure 6.10 provide situational context awareness from the physical sensory information obtained from the patient and the environment. For evaluation of efficient situation, modeling of the relationships between the indoor objects and the entities is necessary.

![Figure 6.10: Graph of entity detection rules for the subset of indoor patient monitoring system.](image)

Figure 6.11 shows the spatial association between the entities and indoor objects or POIs in the present scenario. Although, the qualities such as elevated heart rate and increased perspiration can be obtained at the treadmill, HTHD is a not the applicable entity for the treadmill object. The stove may produce high temperature context and, therefore, the hot environment entity cannot be assessed at the stove.
Similarly, the cold environment is a not applicable at the refrigerator. Identical process can be used to provide relationships between other objects excluded from the present setup and their associate entities. As describe in Chapter 5, these spatial associations can be exploited for efficient situation assessment using equation (6.2).

\[
\text{Situation} \equiv \{\text{Entity(physicalContext)}\} \cap \{\text{applicableEntity(POI)}\}
\]

(6.2)

---

*Figure 6.11: indoor objects to entity relationship for indoor patient monitoring system.*

As described in Chapter 5, the hasNotApplicableEntity is the inverse property of the hasApplicableEntity, therefore, the applicable entities for the indoor objects can also be obtained from Figure 6.11. The utilization of the proposed framework for this patient monitoring system can be explained in Table 6.1.
Table 6.1: Context data for observation (a).

<table>
<thead>
<tr>
<th>Quality-type</th>
<th>Data</th>
<th>Quality</th>
</tr>
</thead>
<tbody>
<tr>
<td>Location (patient)</td>
<td>Treadmill</td>
<td>-</td>
</tr>
<tr>
<td>Heart rate</td>
<td>140 bps</td>
<td>elevated-heart-rate</td>
</tr>
<tr>
<td>Galvanic skin response</td>
<td>12 Seimens (KOhms)</td>
<td>increased-perspiration</td>
</tr>
<tr>
<td>Temperature (patient)</td>
<td>85 °F</td>
<td>temp-high</td>
</tr>
<tr>
<td>Temperature (stove)</td>
<td>60 °F</td>
<td>stove-temp-low</td>
</tr>
</tbody>
</table>

Table 6.1 shows qualities from the observation (a) obtained at the treadmill. The entities from the physical context information are $hotEnv$, $stoveOff$ and $HTHD$, using the rules described in Figure 6.10. Similarly, $hotEnv$, $coldEnv$, $stoveOff$ and $stoveOn$ are applicable entities at the treadmill. The location based situation comprehension can be obtained by utilizing the entity-object relationship given in equation (6.3).

\[
Situation \equiv \{hotEnv, stoveOff, HTHD\} \\
\quad \sqcap \{hotEnv, coldEnv, stoveOff, stoveOn\} \\
\quad \equiv \{hotEnv, stoveOff\}
\quad (6.3)
\]

The result provides significance of the location-based optimization of the entity identification results, as HTHD is not identified as a possible candidate for the situation. The certainty of the assessed situation can be calculated using the methodology described in Chapter 5.
Table 6.2: Context data for observation (b).

<table>
<thead>
<tr>
<th>Quality-type</th>
<th>Data</th>
<th>Quality</th>
</tr>
</thead>
<tbody>
<tr>
<td>Location (patient)</td>
<td>Stove</td>
<td>-</td>
</tr>
<tr>
<td>Heart rate</td>
<td>65 bps</td>
<td>regular-heart-rate</td>
</tr>
<tr>
<td>Galvanic skin response</td>
<td>15 Seimens (KOhms)</td>
<td>normal-perspiration</td>
</tr>
<tr>
<td>Temperature (patient)</td>
<td>85 °F</td>
<td>temp-high</td>
</tr>
<tr>
<td>Temperature (stove)</td>
<td>100 °F</td>
<td>stove-temp-high</td>
</tr>
</tbody>
</table>

The qualities obtained from observation (b) are displayed in Table 6.2 while the patient is at the stove. The coldEnv, normalHealth and HTHD are applicable entities at the stove. The candidate for the actual situation at the stove can be calculated using equation (6.4).

\[
\text{Situation} \equiv \{\text{hotEnv, stoveOn, normalHealth}\} \\
\quad \cap \ \{\text{coldEnv, normalHealth, HTHD}\} \\
\quad \equiv \{\text{normalHealth}\}
\]

(6.4)

6.3.2 Extended indoor disaster management scenario

Section 6.2 explained simplified indoor disaster management scenario with entities such as fire and presence of room heater. In a real world implementation, the mobile sensing platform may consist of additional environmental monitoring sensor with advanced sensing capability for accurate assessment of the situation.
Figure 6.12 gives extended version of the original fire scenario with additional humidity and infrared sensor context and their association with applicable entities. As these environmental sensors have improved precision and ranges, the multiple low-level fuzzy abstractions set can be classified from physical context as compared to just two sets used in the simplified model. Although the availability of enhanced quality abstractions can enable modeling of additional entities, these fuzzy abstractions sets requires precise background knowledge from the domain expert to model these qualities. Figure 6.14 shows that with high temperature and high carbon dioxide context, the fire entity also explains very low or low humidity and high infrared light context. Similarly, additional entity dry ice in the extended scenario, explains qualities such as low temperature, high carbon dioxide and high humidity.

The other context source not modeled in this scenario such as a light bulb, LED, etc. also generates infrared light context. The fire entity produce the infrared context in an extremely significant amount, compared to other entities, which make the fire only appropriate candidate to explain the high infrared context. Distinctively, the high infrared quality can be classified as a discriminating quality.
6.3.3 Weathercasting

Although the framework presented in this research is designed for indoor CPS applications, the uncertainty-modeling component of the framework can be independently ported to outdoor entity identification applications. Patni et al. presented methodology to infer weather conditions from a huge amount of environmental sensory context obtained from the weather stations across the United States[113].

Figure 6.13 displays the reasoning model used by Patni et al. for weathercasting from the raw sensor context. The research utilized crisp abstraction approach to classify temperature, precipitation and wind speed context into respective qualities. According
to model, the freezing temperature quality is strictly defined as 32 °F and applied to all observations containing temperature reading below this limit. In the real world scenarios, the freezing temperature of water is a function of multiple other contexts in the environment such as atmospheric pressure, elevation, wind speed, impurities as solutes, etc. Due to these parameters affecting the freezing conditions, the low-level abstraction of the temperature context demonstrates fuzzy properties and the efficient way to represent that abstraction is through a fuzzy set.

An extension of the model proposed by Patni et al. by introducing the concept of fuzzy abstractions to temperature and wind speed contexts with additional wintry mix entity is presented in Figure 6.14. The figure shows fuzzy sets for temperature, wind-speed qualities and the associated weather condition entities. The ranges for fuzzy sets shown in the figure have been assumed to be obtained from a domain expert. As the original model defines freezing temperature with crisp abstraction below 32 °F, a condition such as flurry occurring at 33 °F is nullified from the reasoning process. For the same condition, using the fuzzy reasoning model displayed in Figure 6.14, the flurry entity can be identified with low certainty number of 0.25. The certainty of flurry entity is calculated using description logic equations (6.5)-(6.7), where raw sensor measurements for temperature, precipitation and wind speed are 33 °F, snow-precipitation and 5 mph, respectively. Utilizing reasoning model displayed in Figure 6.14, situational entities from the observation can be calculated using equation (6.6).
Figure 6.13: Implemented rules by Patni et al. for weathercasting.

\[ \mu(\text{freezingTemp}) = 0.25, \mu(\text{snowPrecipitation}) = 1 \text{ and } \mu(\text{lowWindSpeed}) = 1 \]

(6.5)

\[ \text{Entity} \equiv \{\exists \text{inheresIn.} \{\text{freezingTemp}\}\} \cup \{\exists \text{inheresIn.} \{\text{nonFreezingTemp}\}\}\]
\[\quad \cap \{\exists \text{inheresIn.} \{\text{snowPrecip}\}\} \cap \{\exists \text{inheresIn.} \{\text{lowWindSpeed}\}\}\]
\[\quad \equiv \{\text{blizzard, flurry}\} \cap \{\text{blizzard, flurry}\} \cap \{\text{flurry}\}\]
\[\quad \equiv \{\text{flurry}\}\]

(6.6)
the certainty of the identified situation can be calculated as,

\[
\mu(\text{flurry}) = \mu(\text{freezingTemp}) \land \mu(\text{snowPrecipitation}) \land \mu(\text{lowWindSpeed}) \\
= \min(0.25, 1, 1) \\
= 0.25
\]

(6.7)

The proposed approach also assists in the identification of additional situation such wintry mix, which cannot be explained using the original model. The wintry mix condition explains both non-freezing temperature and freezing temperature from the temperature context. Similarly, the wintry mix condition also explains snow and rain precipitation in environment. Equation (6.8) shows reasoning for the entity wintry mix using description logic.

\[
\text{Explanation(wintryMix)} \\
\equiv \{\exists \text{inheresIn} \{\text{freezingTemp}\} \cup \exists \text{inheresIn} \{\text{nonFreezingTemp}\}\} \\
\quad \land \exists \text{inheresIn} \{\text{snowPrecipitation}\} \\
\quad \land \exists \text{inheresIn} \{\text{rainPrecipitation}\} \\
\equiv \{(\text{blizzard}, \text{flurry}, \text{wintryMix}) \cup \{\text{wintryMix}\}\} \\
\quad \land \{\text{blizzard, flurry, wintryMix}\} \\
\quad \land \{\text{rainStrom, rainShower, wintryMix}\} \\
\equiv \{\text{wintryMix}\}
\]

(6.8)
Figure 6.14: Improved rules for fuzzy semantic abstractions.
6.4 Summary

This chapter presented the comprehensive situation awareness framework via combining contextual situation awareness and spatial entity discrimination results. The components of the frameworks were described with their importance on each optimization stage of the event identification results. The application case of indoor fire presented stepwise implementation of the framework and results obtained from every component. The chapter proposed various application cases which can be deployed to the real world scenarios with the appropriate domain knowledge.
7 Conclusion and Future Work
7.1 Summary

This dissertation introduced a framework to develop situation awareness applications in the cyber-physical domain. This work focused on entity identification task from the environmental context information effectively utilizing the spatial information. The framework was successfully deployed and evaluated for an indoor fire scenario simulated in a controlled laboratory environment.

Earlier in this report, the undeveloped domain of cyber-physical system was introduced with its features, challenges and architecture. The dissertation focused on addressing the challenges associated with the cyber component of the CPSs. The dissertation also addressed the problem of situational awareness in the indoor CPSs in reference to related work. The challenges such as entity identification, interoperability, uncertainty-modeling and location awareness were handled via following contributions.

- The dissertation extended the concept of semantic context abstraction by introducing fuzzy logic to handle uncertainty. The context awareness was achieved via event identification using the fuzzy abductive reasoning. The fuzzy abductive reasoning utilized the fuzzy semantic abstractions to represent the environmental context and explain the entities.

- The interoperability issue was resolved by utilizing semantic annotation and ontologies. The Semantic Sensor Network (SSN) and the domain ontology
assisted in annotation of the raw sensor data and modeling of the reasoning rules.

- The dissertation presented a novel approach of hierarchical modeling of the indoor objects using the indoor location ontology. The indoor location ontology also contained the spatial relationship between the indoor objects and the applicable entities for these objects. The dissertation provided methods of semantic object identification and efficient situation assessment by exploiting the raw spatial information through the indoor location ontology.

- The dissertation introduced the accurate indoor positioning algorithm to provide raw spatial information for the location awareness. Fusion of Radio Signal Strength (RSS) and Time Difference of Arrival (TDoA) signal was used to calculate the environmental loss factor, which was further utilized to estimate the distances and the position of the sensor network node.

- The dissertation presented the system level and semantic modeling components of the compressive situation awareness framework for the indoor CPS. A simplified indoor fire scenario was presented in detail, evaluating the significance of the dissertation contributions. The dissertation also presented guidelines to implement the proposed framework in multiple other CPS applications.
7.2 Future work

Along with methods proposed in this dissertation, the dissertation has enabled new areas of further research in the CPS domain described as following.

7.2.1 Richer spatio-temporal relation modeling between indoor objects and entities

The dissertation provided a step in the direction of modeling the object-entity relationship for situation awareness applications. In some cases, the entity observed at the indoor object has spatio-temporal implications with adjacent indoor objects. Assume a scenario where the physical context information explains HTHD entity at the treadmill. After a moment, the HTHD entity is also detected by the application at the adjacent chair. This phenomenon can be explicitly explained by one of the following cases: (a) patient is resting at the chair after a workout or (b) patient is observing the actual HTHD condition. According to the framework introduced in this dissertation, the HTHD will not be detected at the treadmill and will be detected at the chair from the physical context information observed from the body area sensors. For case (b), the framework will provide appropriate situation comprehension as HTHD at the chair while ignoring the results at the treadmill. In case (a), the elevated heart rate and increased perspiration context are temporal effect of a workout at the treadmill. As modeling methods for this spatio-temporal relationship are not provided in the proposed framework, the system will provide false alarm by detecting HTHD in case (a). As a future work, the dissertation can be extended in the direction of providing efficient
modeling methods for these types of spatio-temporal relationships in the indoor location ontology.

The properties such as hasApplicableEntity and hasNotApplicableEntity modeled the object-entity relationship in the indoor location ontology. In this dissertation, these properties contained generalized relationships specific to application requirements. For example, as described in Chapter 6, the fireplace has fire and the treadmill had HTHD as the not-applicable entities modeled in the indoor location ontology. In a real world scenario, chances of these not-applicable entities occurring at those objects cannot be ignored. Although probabilities of these events to take place at those locations are minor, a richer modeling mechanism is required for efficient entity identification. A combined approach of introducing additional object-entity relationship properties and improvised fuzzy context abstractions can provide appropriate situation awareness results.

7.2.2 Efficient coverage space for the indoor objects

The dissertation used cuboid as the standard shape to represent the operational space occupied by the indoor objects. In the real world scenarios, these indoor objects may have complex coverage spaces with shapes fluctuating according to the application requirements. A future work is required to model various coverage spaces in the indoor location ontology with their limitation in the Cartesian coordinate system. For example, a spherical coverage space can be modeled via specifying the coordinates of the center and the radius. The future work can be also extended to address scenarios where the operational space of two indoor objects overlaps.
7.2.3 Accurate indoor localization via smartphones

As described in Chapter 2, the CPS is a successor technology of the wireless sensor networks and therefore, the dissertation utilized the wireless sensor network assisted indoor localization system to utilize existing CPS components. The mobile CPSs and cyber-physical-social domains are emerging as the popular categories of the CPS implementations. The future implementation of the CPS will include smartphones as the primary mobile platform to acquire the environmental context information. For these applications, smartphone assisted accurate indoor localization will be required due to inconvenience of mounting the sensor mote to the smartphones and having an independent localization technique assisted by the wireless sensor network.
References


[61] S. Perera, C. Henson, K. Thirunarayan, A. Sheth, and S. Nair, “Data driven knowledge acquisition method for domain knowledge enrichment in the


