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Development of Secured Context Rough Ontology Modelling for Ensuring Data Consistency and Integrity

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Abstract. Context awareness enables service discovery and adaptation for ubiquitous computing devices. The inherent noisy nature of environments does not guarantee the sensors present in the ambient, semantic environment to provide relevant data and knowledge representation. Data acquired may be precise or vague and this can be characterised based on subjective. To tackle this problem, we proposed a rule based type 2 Fuzzy Rough Context Ontology Model. We also proposed an adaptive, autonomous and efficient rule acquisition context aware middleware to give integrity with consistent data and representing knowledge in a secured manner.

Keywords: Context awareness, Ontology, type 2 fuzzy rough, middleware.

1 INTRODUCTION

The term Ubiquitous Computing, introduced by Weiser [1], refers to the seamless integration of devices into users' in everyday life. This term represents an emerging trend towards environments composed of numerous computing devices that are typically mobile or embedded and that are connected to a network infrastructure composed of a wired core and wireless edges. Context awareness enables service discovery and adaptation for ubiquitous computing devices. The term "context awareness" was first explicitly introduced in the research area of pervasive computing in [3] It refers to the ability of computing systems to acquire and reason about the context information and adapt the corresponding applications accordingly. Context is a key issue for many research communities like ambient intelligence, real time systems or mobile computing, because it relates information processing and communication to aspects of the situations in which such processes occur. Context can also be specified with different granularities for Semantic Web information items like Web documents (or fragments of documents), ontologies (fragments of ontologies, sets of concepts) Software agents processing them and Semantic Web Services. A context-aware system should automatically recognize the situation using various sensors. Therefore different user devices need semantically rich descriptive context models to provide shared understanding. Moreover, handling user query is another area where semantic knowledge is necessary. Thus, for processing context data, we need more intelligent systems that are capable of processing not only contents but also the meanings (semantics) of data.

Therefore, context modelling is an important feature in context aware systems.

Ontologies, as explicit formal specifications of the terms in a domain and the relations among them Gruber, 1993[40], are a widely accepted tool for modelling context information in pervasive computing domain. The reason for this acceptance is **:** (a) it has several advantages over other traditional modelling approaches [41] and (b) the Semantic Web languages and tools have clearly gained maturity over the past years. In context aware computing, knowledge representation to user is vague or uncertain which harms users' confidence in using context aware applications. This kind of system will lead to insecure knowledge representation. Moreover, it is well known that many real time context aware applications require support for managing this imprecise vague context to avoid inconsistency and integrity. Intelligent solutions are needed to cope up with the fuzziness of context information and, especially because of mobility, rapidly changing environments and unsteady information sources. Several methods have been proposed and applied to deal with vague contextual information [2]. The notion of uncertainty or vague knowledge representation to user in Context Aware computing appears mainly as a consequences of the complexity of context acquisition, context processing and context representation. To handle this uncertainty, we proposed a context aware middleware to deal with vague knowledge through ***Type-2 fuzzy rough*** context ontology rules. Efficient rules in context aware computing can be used both for improving the quality of context information as well as for deriving higher-level probabilistic contexts. The rules can also be used for resolving conflicts between context information obtained from different sources. Such rules not only cope with the imprecise knowledge, but also with the user behaviour and his/her historical context. In this paper, we also perform the adaptation process by using ***Type-2 fuzzy rough*** to define user's context and rules for adopting the policies of implementing a service through effective rule acquisition.

This paper is organized as follows: in Section 2, we discussed related work in the proposed domain. Section 3 describes the basic issues of our approach. Furthermore, section 4 illustrate the associated concepts related to the ***Type-2 fuzzy rough*** context ontology modelling. In Section 5, the detailed procedure of proposed type – 2 fuzzy context ontology modelling is discussed. Section 6, illustrates an experiment with a case study. The experiment results of our approach are shown in Section 7. Lastly, Section 8 presents our conclusions.

2 RELATED WORK

Context information is naturally vague and uncertain. Uncertainty in context information is traditionally handled by appropriate models, as proposed by Chalmers *et al.* [11], who represent context values by intervals or sets of symbolic values. Other approaches such as [12] deal with uncertainty using fuzzy logic. But, they do not concentrate on exact service to user context. Service ought to consider uncertainty represented in their models. We argue that fuzziness on context information must be considered when selecting services. In literature, many platforms were proposed to facilitate adapting context-aware services. The Chisel system [13] introduced a dynamic services adaptation framework which decomposes the particular aspects of a service object into multiple possible behaviours. Whenever the context information changes, the service object will be adapted. To use the different behaviours according to the adaptation policy. Hongyuan et.al.[7] present a rule-based context-aware adaptation model. Although a rich landscape in adaptation related researches, a complete and generic context-aware adaptation approach is still missing. Several surveys dealt with service composition. Many of them classified the middleware under exclusive criteria such as manual versus automated, static versus dynamic, and so on. Others [14] classified the service composition middleware under different domains such as semantic web, artificial intelligence, formal methods, *ambient intelligence* and so on. But none of these works proposed a generic reference model to describe the service composition middleware in pervasive environments.Ontologies are a widely accepted tool for the modelling of context information. Bei Wang et al. [6] build up a self-guided ontology-based mobile information management model for the context. Ejiguet al. [42] discuss some recent achievements in the area of ontology-based context modelling in order to determine the important steps necessary to fully exploit ontologies in pervasive computing. Lee and Kwon [58] model contexts which are generally distributed in smart home environment using the ontology technology. Bandara et al. [59] presents context model ontology for dynamic service context and an operator calculus for integrated and coherent context manipulation, composition and reasoning. Zhang et al. [60] create an ontology-based context model for emotion recognition using EEG for emotion recognition in an intelligent web. Sudhana et al. [61] describes the ontology-based framework for context-aware adaptive learning system, with detailed discussions on the categorization contextual information and modeling along with the use of ontology to explicitly specify learner context in an e-learning environment. Xu et al. [62] present a general and extensible context-aware computing ontology (CACOnt) for modeling context and providing inference mechanisms. Yang *et al.* [9] provide an ontology based context model to represent context and utilize the context to assist service discovery. Mokhatar*et al.* [10] propose the use of ontologies in Semantic Web Ontology Language (OWL-S) for the semantic description of functional and non-functional features of services in order to automatically and unambiguously discover such services. In ubiquitous computing devices Context awareness facilitates service discovery and adaptation. Eleni al. [44] present an ontology-based context modelling, reasoning process and management developed for composing context-aware Ubi Comp applications from Ambient Intelligence (*AmI)* artefacts. Laura Maria [4] proposes support for the design and implementation of a controlling service for context-aware applications by using Jess, a tool for developing rule-based systems. Georgalas [43] proposed ontology based reusable context model. This model facilitates the context reasoning by providing structure for contexts, rules and their semantics ontology. Wonil et al. [46] introduces Multi-layered Context Ontology Framework (MLCOF) based on rules for comprehensive, integrated context modelling and reasoning for object recognition. Lagares et al. [45] present RING, a context-aware ruled-based recommender system for the automatic redirection of incoming communications based on Semantic Web, that permit users to receive any kind of communication through the best channel available depending on his context and personal preferences. Alessandra et al. [5] illustrates a hybrid approach where ontological reasoning is loosely coupled with the efficient rule-based reasoning of middleware architecture for service adaptation.Zarandi et al. [8] developed a type-2 fuzzy rule based expert system for stock price analysis. Interval type-2 fuzzy logic system permits to model rule uncertainties and every membership value of an element is interval itself. In our approach, adapting is through selecting the best rules for service implementation and recursively creating new rules (composites services) to new utilization contexts. This paper presents *Type2 fuzzy rough* ontology-based approach for developing context-aware middleware for the following reasons [46,47]: (1) A well-defined, unified ontology enables knowledge sharing and reuse. (2) Ontologies with declarative semantics provide multiple policies to support context inference. (3) Ontologies provide various complex efficient inference mechanisms to deduce high-level contexts from low-level, raw context data, and to check inconsistent contextual information due to imperfect sensing. (4) Explicitly represented ontologies enhance the development of context-aware systems with semantic web technologies.

3 PROBLEM STATEMENT

In context aware systems, meeting user requirements involves a thorough understanding of their interests expressed explicitly through search engine queries or implicitly through browsing behaviour and search context. We consider that the user is not always able to describe the suited services due to the dynamic change of his context. Nevertheless context information is naturally uncertain and incomplete due to the uncertainty of measuring or to the fuzziness in elucidation. The term "uncertainty" refers to a variety of forms of imperfect knowledge, such as incompleteness, vagueness, randomness, inconsistency and ambiguity. Uncertainty is an important characteristic of data and information handled by real world context aware applications. Currently available Semantic Web technology still provides inadequate foundations to handling uncertainty.

One of main achievements of the Semantic Web initiative was the development of standardization of common web ontology language – OWL. While OWL data types provide means for including numeric uncertainty measures and necessary structural foundations ad hoc, there is no standardized way of representing uncertainty. A well-defined context model without any uncertainty is an important key to access the context in any context-aware system [51]. For instance, Gu et al. [52] presented an ontology-based context model to derive high-level contexts from low level context data. However, most of ontology-based context models fail to represent uncertainty [51]. There is a wide spread opinion that for adequate representation of uncertainty in OWL, some language extension is necessary, be it at the level of language syntax or of higher-level patterns. An example of the first is Fuzzy RDF [57], which extends RDF from triple to couple (value, triple), adding to the triple a ”value”. In contrast, Fuzzy OWL [56] is based on fuzzy description logics; a simple extension to OWL syntax has already been proposed to represent it. There are also approaches based on modelling probability. BayesOWL [53] extends OWL using Bayesian networks as the underlying reasoning mechanism and probabilistic model. PR-OWL [54] is based on MEBN Theory (Multi-Entity Bayesian Network). There is also an approach based on using ontology patterns to define n-ary relations described in ”Best Practices” W3C document [51] that can be applied to uncertainty and in principle consists of creating ad hoc properties and classes for every ontology and every type of uncertain information described by ontology. This however results in inability to use any generic uncertainty reasoner. If one needs to introduce uncertainty handling to an existing ontology, it is necessary to do re-engineering of such ontology (removing classes and properties and creating new ones), which renders the new ontology. Our approach provides *Type2 fuzzy rough ontology* modelling for various kinds of uncertainty. Our design of the context attempts to address challenging issues such as developing explicit ontology representations of contexts, supporting context reasoning and maintenance through logic inferences. Our model aims to provide a concrete and consistent architecture without any inconsistency or vagueness.

4 ASSOCIATED CONCEPTS

The basic concepts that are covered in this chapter are: Semantic web,type-2 fuzzy sets, membership functions and ***Type -2 fuzzy rough*** ontology.

4.1 Semantic Web Layer

Information is everywhere on the internet of things(IoT). Information is essentially data that makes sense. The database community has been working on database integration for some era. They detect many challenges including interoperability of heterogeneous data sources. They used schemas to combine the various databases [15]. Now with IoT, one needs to integrate the diverse and disparate data sources. The data may not be presented in databases. It could be in files both ordered and unordered. Data could be in the structure of tables or in the type of text, images, audio and video. Essentially one needs the semantic web services to integrate the information on the web. The challenge for security researchers is how does one integrate the information securely and interoperate the data effectively? For example, in [16] and [17] the schema integration work of Sheth and Larson was extended for security policies. That is, different things have security policies and these policies have to be integrated to provide a policy for the federated databases system. One needs to examine these issues for the IoT. Each entity in the IoT web may have its own policy. Ontologies are playing a major role in information integration among the IoT based on semantic web. “Semantic Web” with various layers was coined by Tim Berners Lee [23] and the overview is given in Table I.

Table 1 Layers in semantic web

Trust Management layer.	The final layer is sense, proof and trust. The thought here is how do you trust the information on the web? Obviously it depends on whom it comes from. How do you hold out trust negotiation? That is interested parties have to communicate with each other and determine how to trust each other and how to trust the information acquired on the web. Closely related to trust issues is security and will be discussed later on. Logic-based approaches and proof theories are being examined for enforcing trust on the semantic web
Ontologies and Interoperability layer.	Ontologies facilitate information exchange and integration. Ontologies are used by web services so that the web can provide semantic web services to the humans. Ontologies may be specified using RDF syntax.
RDF (Resource	RDF essentially uses XML syntax but has support to express

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Description Framework) layer.	semantics. One needs to use RDF for integrating and exchanging information in a meaningful way on the internet of things. RDF is only a specification language for expressing syntax and semantics.
XML (eXtensible Markup Language) layer	XML is the standard representation language for document exchange. XML is a markup language that follows certain rules and if all documents are marked up using XML then there is uniform representation and presentation of documents. This is one of the significant developments of the World Wide Web. Without some form of common representation of data, it is impossible to have any sort of communication on the web. XML schemas essentially describe the structure of the XML documents. Both XML and XML schemas are the invention of Tim Berners Lee and his consortium called the World Wide Web Consortium (W3C), which was formed in the mid-1990s .Now XML focuses only on the syntax of the document. Data in a document could have different interpretations at entities. This is a major issue for integrating information seamlessly across the Internet of things. In order to overcome this significant limitation, W3C started discussions on a language called RDF in the late 1990s.
Protocols for communication	TCP/IP, SSL and HTTP are the protocols for data transmission.With these protocols one can transmit data over the Internet of Things. At this level one does not deal with syntax or the semantics of the documents.

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4.2 Type-2 Fuzzy Sets

In this section , we define *Type 2 Fuzzy* System and some important associated concepts. This overview is intended to provide the basic concepts needed to understand the methods and algorithms presented later. Type-2 fuzzy sets were first proposed by Zadeh [33] in 1975. But the characterization of type-2 fuzzy sets was first done by Mendel and Liang in 1999 [34]. They characterized type-2 fuzzy sets using the concept of footprint of uncertainty (FOU) and upper and lower membership functions. The type-2 fuzzy set is three dimensional whereas type-1 is two dimensional. The extra dimension allows handling the possible uncertainties. Imprecise perception-based data can be best modelled by using type-2 fuzzy logic [35]. Mendel proposed the use of type-2 fuzzy sets and type-2 fuzzy logic systems to deal with the different types of uncertainties [36]. Type-2 fuzzy sets help us to deal with the uncertainty about the meaning of the words and uncertainties about the consequent used in a rule. Type-1 fuzzy sets cannot deal with this type of uncertainty because the degree of membership is considered as certain in type-1 fuzzy sets. **Figure** .1 shows footprint of uncertainty (FOU) for a Gaussian membership function having a fixed standard deviation, σ, and an uncertain mean that takes on values in [*m1*, *m2*]. The example shown in **Figure** .1 depicts a case where the FOU is uniformly shaded. It means that at each point in the FOU, the membership degree is one. This type of membership functions is known as interval type-2 membership function.

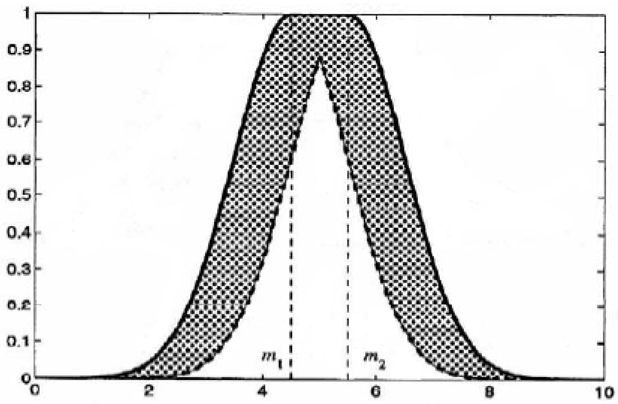

Figure .1. Gaussian Membership Function FOU

A fuzzy logic system is considered to be type-2 as long as any one of its antecedent or consequent sets is type-2. A detailed description of all the components and uncertain rule based fuzzy logic (type-1 and type-2) system are provided by Mendel [36].

4.3 Basis of Type2 Fuzzy Rough

Using the concepts of lower and upper approximations in rough set theory [48], knowledge hidden in information systems may be discovered and expressed in the forms of decision rules [49]. Two types of decision rules usually may be derived, they are, a) based on the lower approximation of a decision class; b) based on the upper approximation of a decision class. To begin with, several necessary concepts of information system are introduced in [50].

Definition 1: *Information system* $<U, A, V, f>$

An information system is an ordered quadruple $<U, A, V, f>$, where U is a non-empty finite set of objects, $A=C \cup D$ is a non-empty finite set of attributes, C denotes the set of condition attributes and D denotes the set of decision attributes. $C \cap D = \Phi$, V is the union of attribute domain, and $f: U \times A \rightarrow V$ is information function associating a unique value of each attribute with every object which belongs to U. If a is an attribute in A $(a \in A)$, xi an object in U $(xi \in U)$, then $f(xi, a)$ denotes the value of object xi of attribute a.

Definition 2: *Rule confidence degree and rule support degree:*

Rule acquired in the information system usually has two kinds, namely, consistent rules and inconsistent rules. Generally, a consistent rule can be denoted by the following format:

$<Condition\ 1 |\ Condition\ 2\ | \ldots \ldots | Conditionn \rightarrow Conclusion>$

Whereas the inconsistent rule is more complicated, with a confidence degree a $(0<=a<=1)$ introduced to denote the rule by the following format:

$<Condition\ 1 |\ Condition\ 2\ | \ldots \ldots | Condition$ □$Conclusion\ a>$

In an information system $<U, A, V, f>$, $A=C \cup D$, acquired rules always have forms like $Des(E_i,C) \rightarrow Des(E_j,D)$, $E_i \cap X_j \neq \Phi$, and the confidence degree a of rule as well as the support degree u of rule are defined below:

$a = |E_i \cap X_j| \,/\, |E_i|$

$u = |E_i \cap X_j| \,/ |U|$

$E_i \in U/IND(C), X_j \in U/IND(D), E_i$ is the condition equivalence relation class, X_j is the decision equivalence relation class in information system, and U is the universe(a finite set of objects). Obviously, the confidence degree of consistent rule is equal to 1; whereas the confidence degree of inconsistent rule is between 0 and 1. The initialization value of a and u is proposed in advance by the user.

Definition 3: *Incomplete information system* :

$<U, A, V, f>$ is called an incomplete information system if V contains null value for at least one attributes $a \in A$, otherwise it is complete. Further on, we will denote null value by *, that is $f(x_i, a) = *$.

Definition 4: *Similar relation:*

Let $B \subseteq A$, then a similar relation is derived from B: $SIM(A)=\{ (x, y) \in U \times U \mid \forall a \in B, f(x, a)=f(y, a)$ or $f(x,a)=*$ or $f(y, a)=* \}$.

Definition 5: *Lower approximation and upper approximation:*

Let $X \subseteq U$, $B \subseteq A$, BX is lower approximation of X, iff$BX=\{x \in U \mid SIMB(x) \subseteq X\}=\{ x \in X \mid SIMB(x) \subseteq X\}$; B

$\overline{X}$ is upper approximation of X, if fB

$\overline{X}=\{x \in U \mid SIMB(x) \cap X \neq \Phi \}=\cup\{ SIMB(x) \mid x \in X \}$.

5 ARCHITECTURE

The proposed context-aware middleware architecture, showed in **Figure** .2, constitutes five layers: at the lowest layer we have access to different computational entities (Smart phone, wearable computer, and tablet) and diverse sensors and actuators devices (RFID,

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camera, and marker). Next layer is an interface allowing two ways exchange between devices and middleware management layer. Third layer is autonomous middleware management layer which contains an adaptive reasoning engine, a context knowledge base (KB), a context database and a context query engine. Next layer is a high level user context aware security interface between the middleware and the application layer. We propose to describe more precisely the management layer in which the reasoning engine is the brain of the context aware middleware.

<table>
<tr><td colspan="4">Application Layer</td><td>Level 5</td></tr>
<tr><td colspan="4">User Context aware Security Layer</td><td>Level 4</td></tr>
<tr><td>Reasoning Engine</td><td rowspan="2">Middleware</td><td rowspan="2">Context Query Engine</td><td rowspan="2">Context Data Base</td><td rowspan="2">Level 3</td></tr>
<tr><td>Context Knowledge Base</td></tr>
<tr><td colspan="4">Sensor Data Fusion and
Secure Information Interoperability Layer</td><td>Level 2</td></tr>
<tr><td colspan="4">Sensor Layer for Internet of Things</td><td>Level 1</td></tr>
</table>

Figure 2. Context-Aware Middleware Architecture

A. Sensor Layer

At the bottom are *sensors* that deliver raw sensor data. They may be wireless sensor networks, video cameras for tracking, RFID tags for identification, ultrasonic badges for location, or others. These produce raw sensor data, often pre-processed for saving communication cost as much as the (often power-constrained) sensor devices allow. These data are passed up one stage in the framework to the Sensor Data Fusion.

B. Sensors data fusion and Secure Information Interoperability Layer

It collects and integrates secure information from the divergent sensors and send appropriate information to the context Database;

C. Context database

It stores the context data (low level context)from sensors data fusion;

D. Context query engine

It handles the query from the application;

E. Context knowledge base

It stores the context model(environment context and users' context) by the ***Type-2 fuzzy rough*** ontology based model.

F. Reasoning Engine:

Context-aware systems must be able to perform context reasoning to facilitate dynamic adaptation to the changing environment, i.e. to be context-aware. ***Type-2 fuzzy rough*** Ontology based reasoning is proposed in the architecture. The proposed reasoning engine is organized as hybrid multi-level extendable engine: a strategy reasoning engine based on ontology reasoning and the detail reasoning engine based on ***Type-2 fuzzy rough*** decision tree reasoning. According to the collected raw data from sensors, reasoning engine exploring environment context and user context is able to take strategic appropriate decision. Then more precise reasoning can occur based on ***Type-2 fuzzy rough*** context decision tree. Here, a number of nodes can be combined to provide different decision paths based on information supplied by the sensors and context database. These nodes can communicate with context database, allowing up-to date information to be retrieved. The proposed model provides rule inference and acquisition capabilities based on ***OWL*** which can combine with semantic web rule-based systems to improve reasoning capabilities. Following are the functions performed by our proposed reasoning engine:

- Based on the reasoning rules that are defined by the user himself or the developer, context-aware systems can proactively provide context-aware services
- On the basis of our ***Type-2 fuzzy rough*** context ontologies, reasoning engine removes uncertainty, ambiguous and inconsistent data. It checks the context consistency and deduces the high-level context from low-level context thereby verified through rule-based reasoning.
- Rules acquisition from high-level, implicit contexts includes entailment rules and user-defined rules.

In this way we get a more bendable, robust, and efficient problem resolution in complex ambient intelligence situations.

G. User Security Layer

User security layer focuses on the access control issues. The goals of designing and developing access control mechanisms contingent upon various environmental and application-dependent contexts with secure provision for delegation of access control rights. This layer advocates a hybrid approach based on ***Role, Status, Kerberos, Network RSKN authentication service by discretionary access control DAC, role-based Access Control RBAC and context-aware access control.*** This layer consists of ***Security Manager*** and ***Context aware manager.***

1) ***Security Manager***

Security Manager runs single authentication and consists of sub-modules as follows:

• *Security Agent*: collects user authentication information when users log in the system or network.

• *Security Gateway*: Installed in security server, and processes user authentication with user authentication information of Security Agent.

2) ***Context-Aware Manager***

Context-Aware Manager performs the access control process and essentially composed of four processes: (i) ***Identification*** (ii) ***Authentication*** (iii) ***Authorization*** and (iv) ***Access decision***. The four processes are performed in the any or all of the following sub-modules in Context aware manager,

- *Context-Aware Process:* related to access resource, access context and user permission,. It inquires authentication process with context-awareness.
- *Repository:* Saves context information collected during user authentication, intrusion detection and response time.
- *Role Based Access Control (RBAC)*: Accesses control settings for each resource.
- *Security Process Rule:* Defines user authentication procedures and roles.
- *User Authentication Analysis:* Analyzes the user's permission.
- *Access Context Analysis:* Analyzes user access network and time context.

- *Access Resource Analysis:* Analyzes access permission for the access resource.

i. *Data Flow between User and Security System*

By examining the data flow between the user and context-aware security system, the security manager transfers the information, which is acquired when the user logs in, such as ***user ID, IP address, IP address of the resource being accessed, access time***, and other relevant information to a ***context-aware manager***. The ***context-aware manager*** (security server) determines the security level based on the context information, then transfers security process (authentication procedure and access control information) and process Information (process blocking information) to the ***security manager***. If the authentication succeeded, the user can proceed further.

ii. *Dynamic Analysis of Context Information*

A Context-aware security system consists of an ***OSGi*** service platform based bundles, thereby dynamically analysing context information for each different domain. By using the dynamic analysis, it allows the system to lessen the system overhead due to its flexible application of security service according to various field statuses.

H. Application Layer

This layer gathers information specific to the application allowing the designer to describe:

- All relevant contexts to which the application is sensitive by creating instances.
- Context-aware components belonging to the application by creating instances and binding them with the described relevant context using their properties.
- Interpretation rules for indirect context description, by creating instances of the class to describe interpretation methods and the property which enables to specify the indirect context to be deduced using context information.
- Reactive adaptation of the application, when a relevant context is detected, by describing the property which binds relevant context with the associated adaptation method class.
- Proactive adaptation of the application, by describing the property which binds relevant context with the policy to be invoked as instance, and the component ,which invokes the relevant service.

6 METHODOLOGY

6.1 Design Considerations

The implementation of context-awareness is made possible by a combination of different technologies. First, the system needs appropriate data collection technologies for sensors and fusing technologies at a higher level for analysing and interpreting sensor data. Decoupling the sensing layer from applications is a key design principle for context-aware applications. To this end, software frameworks are needed to simplify and standardize (using appropriate patterns) the communication between applications, sensors and actuators. Moreover, to maximize the usefulness of context information for different services, designers need to create standard and widely accepted models with standard mechanisms in together for accessing these models for context information.

6.2 Context Modelling and Reasoning

6.2.1 Ontology-Based Context Modelling Approach

We have chosen ontology based models because they constitute a standard representation, reasoning and inferring scheme of knowledge. OWL language is chosen for representing information about objects and relationships relevant for the Context-aware service task. The main advantage of this context model is sharing common understanding of the structure of context information among users. This enables devices and services to enable semantic interoperability to meet the needs of the individual user. It also enables reuse of domain knowledge. Most importantly, it enables formal analysis of domain knowledge. The use of ontology will make our model independent of programming and application environment. In addition to the standardization of the structure of the context representation, it will help us to provide semantic descriptions and relationships of entities.

Generally, the basic idea in rough set theory, [48,49] a vague concept is approximated by means of a pair of concepts. They are as ***upper approximation*** **(R ↑ A)** and ***lower approximation*** **(R ↓ A)**, specifying the set of elements which definitely and possibly belong to vague set. They are as shown in Fig 3.

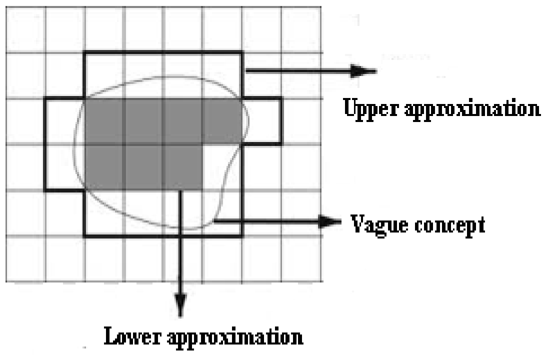

Figure 3. Lower and upper approximations in a rough set

Fuzzy rough sets given fuzzy similarity relation **R**, **t** – norm ⊗ and an implication function ⇒,

Upper approximation of a fuzzy set **A**: for all **x** ∈**X**,

$$(\mathbf{R} \uparrow \mathbf{A})(\mathbf{x}) = \sup_{y \in X} \{\mathbf{R}(\mathbf{x}, \mathbf{y}) \otimes \mathbf{A}(\mathbf{y})\}$$

Lower approximation is defined as: for all **x** ∈**X**,

$$(\mathbf{R} \downarrow \mathbf{A})(\mathbf{x}) = \inf_{y \in X} \{\mathbf{R}(\mathbf{x}, \mathbf{y}) \Rightarrow \mathbf{A}(\mathbf{y})\}$$

This model , cannot be used to analyse deeper knowledge. To achieve this fuzzy rough set offers ***tight lower approximation*** **(R↓↓ A)**, ***loose lower approximation*** **(R↑↓ A)**, ***tight upper approximation*** **(R↓↑A)**, and ***loose upper approximation*** **(R↑↑A)** in type-2 and are defined by the following membership functions :

$$(\mathbf{R}{\downarrow\downarrow}\,\mathbf{A})(\mathbf{x}) = \inf_{z \in X} \mathbf{R}\ (\mathbf{x}, \mathbf{z})\left\{\Rightarrow \inf_{y \in X} \{\mathbf{R}(\mathbf{z}, \mathbf{y}) \Rightarrow \mathbf{A}(\mathbf{y})\}\right\}$$

$$(\mathbf{R}\uparrow\downarrow \mathbf{A})(\mathbf{x}) = \sup_{z\in X} \mathbf{R}(\mathbf{x},\mathbf{z})\{\otimes \inf_{y\in X} \{\mathbf{R}(\mathbf{z},\mathbf{y}) \Rightarrow\} \mathbf{A}(\mathbf{y})\}$$

$$(\mathbf{R}\downarrow\uparrow \mathbf{A})(\mathbf{x}) = \inf_{z\in X} \mathbf{R}(\mathbf{x},\mathbf{z})\{\Rightarrow \sup_{y\in X} \{\mathbf{R}(\mathbf{z},\mathbf{y}) \otimes\} \mathbf{A}(\mathbf{y})\}$$

$$(\mathbf{R}\uparrow\uparrow \mathbf{A})(\mathbf{x}) = \sup_{z\in X} \mathbf{R}(\mathbf{x},\mathbf{z})\{\otimes \sup_{y\in X} \{\mathbf{R}(\mathbf{z},\mathbf{y}) \otimes\} \mathbf{A}(\mathbf{y})\}$$

By using the fuzzy rough concept **C** and fuzzy rough similarity relation **R**, we define these fuzzy rough modifiers [14] in type – 2 as,

exceedingly(C) = $(\mathbf{R}\downarrow\downarrow\mathbf{C})_{KD}$
certainly(C) = $(\mathbf{R}\downarrow\mathbf{C})_{KD}$
very(C) = $(\mathbf{R}\downarrow\mathbf{C})_{Ł}$
somewhat(C) = $(\mathbf{R}\uparrow\mathbf{C})_{Ł}$
relatively(C) = $(\mathbf{R}\uparrow\mathbf{C})_{G}$
nearly(C) = $(\mathbf{R}\uparrow\uparrow\mathbf{C})_{G}$
In addition to that, we may define
indeed(C) = $(\mathbf{R}\downarrow\uparrow\mathbf{C})$
veryvery(C) = $(\mathbf{R}\uparrow\downarrow\mathbf{C})$

The user can carry out Fuzzy Rough knowledge consistency in terms of ***Type-2 Fuzzy Rough*** modifiers such as ***exceedingly, very, veryvery, somewhat, certainly, nearly, relatively***. An advantage of these modifiers is ***flexibility and consistency***. For example : In general, we specify "Sun is *Hot", "Raj is good boy", "Her Presentation is good". But*, in terms of Fuzzy Rough modifier we can clearly indicate "Sun is ***VeryVery*** *Hot", "Raj is **very** good boy", "Her Presentation is **somewhat** good"*.

6.3 Type 2 Fuzzy Rough Ontology Methodology

A. Context information and Classification

Context can be obtained from the source provider directly and or obtained by integration and reasoning of direct context. To describe context classification information in our context, we introduced property element - *owl: classifiedAs* in property restrictions. This element can capture related properties about data types and object in the context classification. The values of the property element are ***Aggregated, Deduced, Sensed or Defined***. After determining classification of property, considering the interdependence between context information, we further analyse the characteristics of context information. To describe restraint in context information by *OWL*, we introduced property *element - rdfs*: *dependsOn* in object properties and data attributes, which is to capture attribute dependence between data types and object.

B. Conceptualization

A class has a name and a set of properties that describe the characteristics of the class, Class is also called "concept", "type", "category" and "kind" in some ontology specification languages. The class can be instantiated by creating Individuals. Property describes an attribute of a class or an individual. A property can also be composed by other properties. For example "*GradeAssesment*" is based on "Evaluator", we define a property "*BasedOn*" for GradeAssessment and assign it to the class "Evaluator". Property is also referred to as "aspect", "attribute", "feature" or "characteristic".

Relation: defines ways in which classes or individuals can be associated with each other. In our ontology definition model, the types of relations are predefined. To express specific relations, we need to use properties. Four types of relations are defined to connect classes and individuals:

a) *Subclass*: extends an abstract class to convey more concrete knowledge.
b) *PartOf*: means a class or an individual is a part of another class or individual.
c) *Complement*: expresses that the members of a class do not belong to another class; and the two classes together contain all the members in a given domain; and
d) *Equivalence*: means that two classes, individuals or properties are exactly the same.

Our context ontology modelling uses axiom such as *owl:subclass, owl:inverseOf, owl:unionOf, owl:disjointWith and owl:sameAs* which are provided in OWL as shown in the following example:

<owl: Class rdf:ID='Evaluator'>
<rdfs:subClassof>
<owl:Restriction>
<owl:onPropertyrdf:resource='Graduat'/>
<owl:toClassrdf:resource ='#Person'/>
<owl:classifiedAsrdfs:resource='ftp://305678/classification#Reference'/>
</owl:Restriction>
</rdfs:subClassof>
</owl:Class>

We generated Type 2 Fuzzy ontology-based context metadata which is stored in the repository and is retrievable by the inference engine. The data which is generated by sensors provides the information used by service inference engine.

c. Building of ontology

The context ontology should be able to capture all of the characteristics of context information. Our context ontologies are divided into high-level and low-level ontologies as proposed [28]. The high-level ontology is a generic ontology which captures basic context knowledge about the physical world environments that includes uncertainty. The low-level ontologies are a collection of domain-specific ontologies which removes uncertainty by ***Type 2 fuzzy rough*** in the form of ***upper approximation, loose upper approximation, tight upper approximation, lower approximation, loose lower approximation and tight lower approximation.***.

1)Type 2 Fuzzy Rough reasoning scheme & Implementation

In this scheme, we use ***Type 2 Fuzzy Rough OWL*** reasoning combined with SWRL reasoning, which ensure reasoning efficiency, and make reasoning have more rationality and decidability. Reasoning by ***Type 2 Fuzzy Rough OWL*** in the form of upper approximation, ***loose upper approximation***, tight upper approximation, ***lower approximation, loose lower approximation*** and ***tight lower approximation*** can build better ontology, and ensure that no conflict happen between definitions. Knowledge and reasoning based on ontology rule relies on rule-based reasoning of *SWRL*. After standardizing terms of definitions, we define various properties in accordance with the requirements of ***OWL***. Subsequently, use OWL to represent ontology model, and introduce ontology knowledge in the description logic inference engine. Then, combined with the particularity of established ontology and reasoning rules, we use ***SWRL*** represent reasoning rules.

2) Rule extracting algorithm for incomplete information system

In terms of improved discernible matrix, the rule extraction algorithm for incomplete information system is described as follows :

Input : The initial incomplete information system $<U,A,V,f>$, $(A=C\cup D)$, $B\subseteq A$, a_0, u_0.

Output : rule set R, $\forall r\in R$, $ra>=a_0$, $ru>=u_0$.

Step 1 : Data pre-treatment;

Step 2 : In terms of condition attributes set $C,B'\subseteq C$, group the decision information system to someobject similar relation classes Si, $Si\in U/SIM(B'),i=1,2,\ldots,|U/SIM(B')|$;

Step 3 : In terms of decision attributes set D , group the decision information system to some decision object equivalence relation classes $Xj,Xj\in U/IND(D),j=1,2,\ldots,|U/IND(D)|$;

Step 4 : Find the minimal attributes reduction withthe optimization andacquire the decision rules.

Step 5 : Based on result of the minimal attributes reduction, induce the decisive rules, that is, when $S_i\subseteq Xj$ is satisfied, the certain rules are obtained; when $S_i\not\subset X_j$ and $S_i\cap X_j\neq\Phi$ are satisfied, the uncertain rule isobtained, where confidence degree a is $|S_i\cap X_j|/|S_i|$,and support degree u is $|S_i\cap_j|/|U|$.

Step 6 : If the acquired rule which confidence degree $a\geq a_0$ and support degree $u\geq u_0$ are respectively satisfied, can be credited as an anticipant rule and output to the rule set, otherwise discard it. If acquired two rules with the same condition attributes have the different decisive attributes, how one is selected is decided by the confidence degree and support degree; if two rules are satisfied, it turns out a decision composite rule.

In this system, we used OWL descriptions of classes, properties and their instances. Given such an ontology, the OWL formal semantics specifies how to derive its logical consequences, i.e. facts that are not literally present in the ontology, but are entailed by the semantics.

D.Evaluation

Quality constraint is a set of parameters which is used to judge the credibility of the information. Considering ambiguity information and possibility of the parameters boundary adjustment, using soft constraint build theconstraint condition of the quality of information. Considering highly dynamic nature of pervasive computing systems and imperfect sensing technology led to information inconsistency at different levels, we constructed quality constraint, an extensible ontology forquality of information, as indicators describing authenticity of context information.Quality constraint is associated with a number of quality parameters, which capture the dimensions of quality relevant to the attributes of entities and relationships between entities.

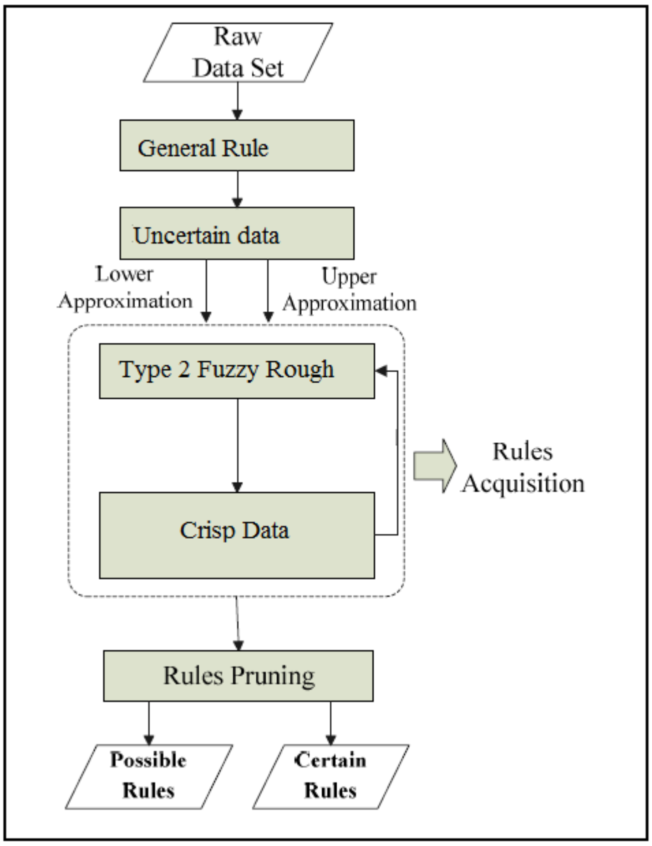

Figure 4 Flow chart for Rule extraction.

Each parameter is described by one or more appropriate quality metrics, which defines how to measure or compute context quality with respect to the parameter. Besides a value, a metric contains a type and a unit.For different type information focused on the difference, and fuzzyness cannot be ignored in the defined information, we have defined quality parameters such as ***accuracy and timeliness*** as the basic quality criterias of context information. The overview of ***Type-2 Fuzzy Rough*** concept modelling Architecture is shown below.

Flow of Architecture

- *Step1 :* Collect sensor data from physical and virtual sensors as xml form file.
- *Step 2 :* Parse input and feed to the Context Acquisition &Fusion.
- *Step3 :* Assimilate the context and input to context interpretation phase
- *Step 4&5 :* Look up the Context Database and repository for such situation has occurred previously and retrieverelevant data according to the context and return to context interpretation
- *Step6 :* Look up the Inference Rules for rules which takes premises existed in the context and returns a conclusion, if it is newly sensed data; learn it and update newly learned data in the database
- *Step 7 :* Context Reasoning Engine query's a request to context representation.
- *Step 8 :* Response to Context Reasoning Engine.
- *Step9 :* Context Engine to perform the action and inputs to API/ Agent.

- *Step10 :* Agent/API sends inputs to the Service server side and generates the alerts/warning signals to the Interface.
- *Step11 :* The action performed from the Service server side is stored in the log database.

7 CASE STUDY –STUDENT EVALUATION CONTEXT USING VAGUE VALUES

Student evaluation is the process of determining the performance levels of individual students in relation to educational learning objectives. A high quality evaluation system certifies, supports, and improves individual achievement and ensures that all students receive a fair evaluation in order not to constrain students' present and future prospects. Thus, the system should regularly be reviewed and improved to ensure that it is suitable, fair, impartial and beneficial to all students. It is also desirable that the system is transparent and automation measures should be embedded in the evaluation. The fuzzy set theory has been widely used in solving problems in various fields, and recently in educational evaluation. In recent years, some methods [20], [21], [22], [24]-[31] for students' evaluation have been presented. In [38.] and [39], the fuzzy marks awarded to answers in the students' answerscripts are represented by fuzzy sets [32].However, if we can allow the marks awarded to the questions of the students' answerscripts to be represented by vague values [37], then there is room for more flexibility. Ontology based model is used in our approach to constitute a standard representation, reasoning and inferring scheme of knowledge. Here, we define a type -2 fuzzy rough ontology in the form of ***upper approximation, loose upper approximation, tight upper approximation, lower approximation, loose lower approximation and tight lower approximation*** to evaluate assess students marks**.** To identify evaluation context we use generic student and evaluator context. **Figure** 5 shows the element for student evaluation context. And then, Table 1 shows the four different parts (means) of evaluation and their respective criteria to be judged by the evaluator. The final grade of a student is computed based on the outputs of four assessment components. The criteria of assessment (indicators of assessment components) are represented by ***Type-2 fuzzy rough*** sets as we believe that these criteria are judged on the basis of perception of an evaluator.

Student elements
Name
S – ID
Course
Grade
Evaluator elements
Name
Position
Assessment
Security elements
Authentication
Authorization
Access control

Fig .5. Ontology Sub concepts

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Table II Assessment Components and Criteria

Assessment Component	Criteria for Assessment
Final Report (FR)	Format and Structure Literary Quality Quality of Subject Matter
Progress Report (PR)	Task Description Format and Submission
Final Presentation (FP)	Content and Organization Speaking (Presentation) Skills Response to Questions
External Evaluation (EE)	Enthusiasm and Interest in Work Ability to Learn and Search for Information Relations with Co-Workers Punctuality and Delivering Work on Time

7.1 Evaluation Model

We propose students' evaluation model based on ***Type-2 fuzzy rough*** ontology. The evaluation information is extracted in the form of ***OWL*** extends with ***SWRL*** rules from evaluators (experts) and these rules are modelled using a ***Type-2 fuzzy rough*** logic system, which then is used as a fuzzy rough logic assessment *FRLA* to make decisions about students' grades. We also propose a two-stage FRLA based on ***Type-2 fuzzy rough*** logic, shown in **Figure** 5, where each assessment component is evaluated using an independent FRLA and then the results of these FRLAs are combined to calculate the final grade of a student using a second-stage FRLA.

7.2 Type-2 Fuzzy Rough Sets for Evaluation

The whole range of input (criteria of assessment) and output (evaluation) attributes are divided into number of fuzzy rough sets. We use four ***Type-2 fuzzy rough*** sets as fuzzy rough modifiers namely ***Excellent, very good ,more or less good and definitely bad*** to represent each criterion of assessment and the output of assessment components of stage-1. The input for the model that we have proposed receives input from the evaluator. In addition to that, "GradeAssesment" is based on "Evaluator". Here, we define a property "***BasedOn***" for GradeAssessment and assign it to the class "***Evaluator***". Property is also referred to as "***aspect", "attribute", "feature***" or ***"characteristic***". Relation: defines ways in which classes or individuals can be associated with each other. Different evaluators may provide different assessments, based on their experience, regarding a particular fuzzy rough set (e.g., Excellent) range of a specific input/output attribute. This causes uncertainty in evaluating the students. To overcome this uncertainty, ***Type-2 fuzzy rough*** sets model is preferred, by blurring the evaluation criteria boundaries and defining the footprint of uncertainty (FOU). For our model, based on *Type- 2 Fuzzy Rough* concepts, a group of evaluators is chosen using a scale range from 0 to 10. Table . III shows the mean and standard deviation values for these range labels based on Type- *2 Fuzzy Rough*. We associate triangle membership function with the modifiers *more or less good* ($\tilde{F}$) and *very good* ($\tilde{G}$), and piecewise linear membership function with modifiers *very very bad* ($\tilde{P}$) and *Excellent* ($\tilde{E}$).

Table III. Survey Results for Labels of Fuzzy Rough Sets

Label	Mean		Std. Deviation	
	Start	End	Start	End
	A	b	σ_a	σ_b
Definitely bad	0	4.7389	0	0.4898
More or less good	4.7056	6.8778	0.4978	0.4295
Very Good	6.6556	8.7222	0.4419	0.3153
Excellent	8.4889	10.0000	0.3296	0.0000

The uncertainty about the words used in antecedents and consequents of rules and uncertainties about the rule consequents are captured in type-2 fuzzy rough sets using FOUs. We obtain FOUs in the form of ***upper, tight upper, loose upper, lower, tight lower and loose lower*** membership function for each fuzzy rough set. These fuzzy rough sets are calculated based on procedure described in [18.]. **Figure** 7 shows the FOUs for the four fuzzy rough sets for ρ=0.5 (50% percent uncertainty), where ρ is the fraction of uncertainty and $(0 \le \rho \le 1)$. Similarly, for stage-2, the output of stage-1 will be used as input in the form of type-2 fuzzy rough set shown above. The output of stage-2 (*Grade*) is also divided into nine different fuzzy rough modifiers namely *Exceptional*, *Excellent*, *Superior*, *Very Very Good*, *Above Average*, *somewhat Good*, *High Pass*, *Pass*, and *Fail*. In our proposed model, the initialization of membership functions is done through singleton input.

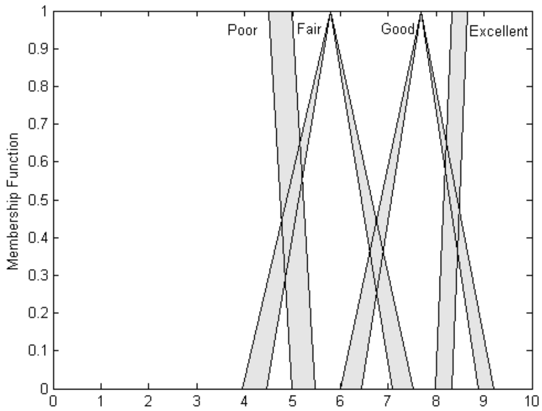

Figure 7. FOUs for Linguistic modifiers

Level 1 & Level 2 Input from Internet of Things	***Level 3 OWL extend with SWRL for IoT and execution of our middleware layer***				***Level 5***
	Fuzzy Rules ***Fuzzy Set Definition*** ***Assessment Criteria***	***Student Evaluation by evaluators***	***Vague result***	***Applying Type – 2 fuzzy rough set in vague result***	***Crisp output***

Figure 6. Two-Stage Type-2 Fuzzy Rough Logic Based Framework for Evaluatio

7.3 Fuzzy Rough Rule Base and Defuzzification

In the rules formulation we follow the approach where all the possible combinations of antecedent fuzzy rough sets are employed. The consequents of rules are provided by the experts (evaluators) through survey. Each rule has a histogram of responses. Our proposed model is composed of five FRLAs and each one has its own set of rules. The number of rules depends on the number of inputs and fuzzy rough sets associated with them. For example, for *Progress Report FRLA*, the number of rules will be 4x4=16. While for *Final Report FRLA*, there will be 64 rules. Maximum number of rules will be for *External Evaluation FRLA* and *Evaluation FRLA* i.e. 256. An example rule for *FRLA* will be of following form:

R_l: IF FR is $\tilde{E}$ AND PR is $\tilde{G}$ AND FP $\tilde{F}$ is AND EE is $\tilde{E}$ THEN GRADE is $VV\tilde{G}D$ (VERY VERY GOOD)

For later calculations, we compute weighted average (C^l_{avg}) of the rule consequents of each rule [12].

The consequent of each rule is treated as type-1 fuzzy rough set. Initially we did survey for small group of experts due to large number of rules. A partial histogram of final report evaluation FRLA with three Evaluations and a result, and corresponding weighted average response for both type-1 and type-2 is shown in table 3. The final output of our proposed FRLAs is a type-reduce interval set, having the following form:

$Y_{TR} = [y_l, y_r]$

where y_l and y_r are computed using following two fuzzy rough basis function (FRBF) expansions .

For a ***Type-2 fuzzy rough*** set $\tilde{F}$, we calculate lower approximation f_l, upper approximation, loose lower approximation f_{ll}, tightlower approximation f_{tl}, loose upper approximation f_{lu} ,and tightupper approximation f_{tu} using following equations:

$$f_l = \min[\mu l_{\tilde{F}1}, \mu l_{\tilde{F}2} ..... \mu l_{\tilde{F}M}] \qquad (1)$$

$$f_u = \min\lfloor \mu u_{\tilde{F}1}, \mu u_{\tilde{F}2} \ldots\ldots \mu u_{\tilde{F}M} \rfloor \qquad (2)$$

$$f_{ll} = \min\lfloor \mu ll_{\tilde{F}1}, \mu ll_{\tilde{F}2} \ldots\ldots \mu ll_{\tilde{F}M} \rfloor \qquad (3)$$

$$f_{tl} = \min\lfloor \mu tl_{\tilde{F}1}, \mu tl_{\tilde{F}2} \ldots\ldots \mu tl_{\tilde{F}M} \rfloor \qquad (4)$$

$$f_{lu} = \min\lfloor \mu lu_{\tilde{F}1}, \mu lu_{\tilde{F}2} \ldots\ldots \mu lu_{\tilde{F}M} \rfloor \qquad (5)$$

$$f_{tu} = \min\lfloor \mu tu_{\tilde{F}1}, \mu tu_{\tilde{F}2} \ldots\ldots \mu tu_{\tilde{F}M} \rfloor \qquad (6)$$

8 EXPERIMENTS AND RESULTS

We implemented ***Type-1*** and ***Type-2 fuzzy rough*** logic assessments (FRLAs) using SCILAB fuzzy logic tool box. We compared our FRLA with the existing evaluation system. In the existing system, same assessment components are used for evaluation but the usage of linguistic labels with the range is fixed. Using these fixed range assessment method, the overall performance of a student is assessed by simply adding their marks in different components. We implemented a fuzzy rough logic assessment based on the inputs of experts for range of different linguistic variables for evaluation (shown in table 2). Our system uses the rule-based fuzzy rough inference system to calculate the overall grade of a student which provides more accurate evaluation of a student as compared to existing method. We found that the uncertainties in the representation of criteria for assessment (linguistic variables) can be well taken into account by using ***Type-2 fuzzy rough*** sets. For verification of our model, we selected a sample of students' evaluation and compared the outputs of the individual's FRLA with the output of our proposed consensus type-1 and type-2 FRLAs. For this purpose same assessment components and criteria were used. **Figure** 8 shows a comparison for the outputs of individual and consensus type-1 FRLAs for final report (FR) evaluation. This plot shows that the outputs of individual and consensus FRLAs differ marginally for most of the students. **Figure** 9 and **Figure** 10 show the comparisons for outputs of individual and consensus type-2 FRLAs for the same assessment component (FR) with 50% and 100% uncertainty. These two plots depict that the individual assessment lies in between the limits of consensus assessment (left-hand and right-hand curves) which reflects that type-2 based system captures all those uncertainties which are there due to words in surveys and consensus consequents. Our experimental results also provide efficient time and accuracy.

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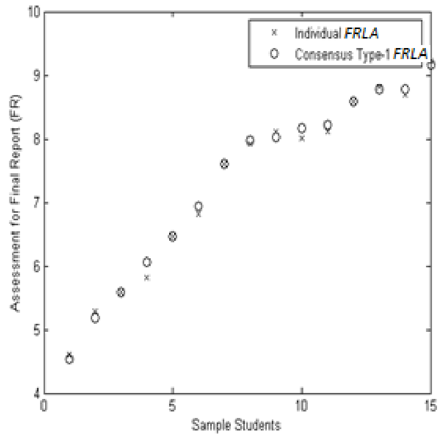

Figure 8. Comparison for Individual and Type-1 Consensus FRLAs

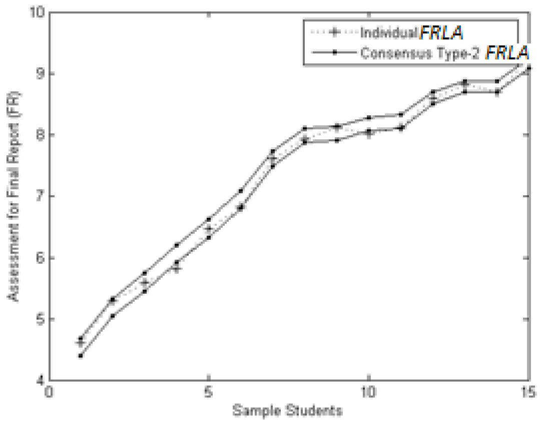

Figure 9. Comparison for Individual and Type-2 Consensus FRLAs (50% uncertainty)

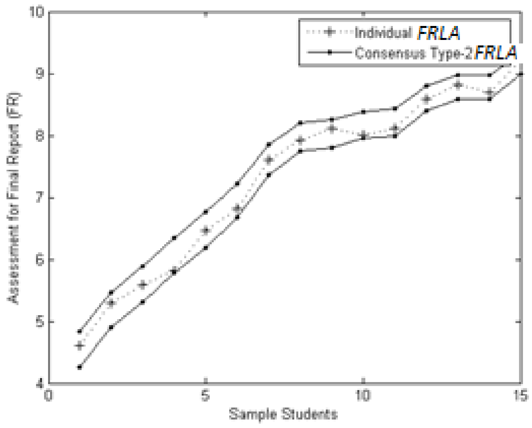

Figure 10. Comparison for Individual and Type-2 Consensus FRLAs (100% uncertainty)

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Table IV. Partial Histogram of Survey Responses for Final Report Evaluation

Rule No.	Evaluation 1	Evaluation 2	Evaluation 3	Grade Result: Excellent	Grade Result: Very Good	Grade Result: More or less good	Grade Result: Definitely bad	Type-1: C_{avg}	Type-2: C^{l}_{avg}	Type-2: C^{r}_{avg}
1	Excellent	Excellent	Excellent	8	0	0	0	9.162	9.077	9.242
2	Excellent	Excellent	Very good	6	2	0	0	8.783	8.688	8.874
3	Excellent	Excellent	More or less good	4	3	1	0	8.17	8.061	8.276
4	Excellent	Excellent	Definitely bad	0	5	2	1	6.533	6.4	6.666
5	Excellent	Very good	Excellent	6	2	0	0	8.783	8.688	8.874
6	Excellent	Very good	Very good	3	4	1	0	7.98	7.866	8.093
7	Excellent	Very good	More or less good	0	5	3	0	6.943	6.806	7.079
8	Excellent	Very good	Definitely bad	0	4	3	1	6.298	6.162	6.435
9	Excellent	More or less good	Excellent	2	5	1	0	7.791	7.671	7.909
10	Excellent	More or less good	Very good	0	6	2	0	7.178	7.044	7.311
11	Excellent	More or less good	More or less good	0	5	3	0	6.943	6.806	7.079
12	Excellent	More or less good	Definitely bad	0	2	5	1	5.829	5.686	5.972
13	Excellent	Definitely bad	Excellent	0	3	4	1	6.064	5.924	6.204
14	Excellent	Definitely bad	Very good	0	3	4	1	6.064	5.924	6.204
15	Excellent	Definitely bad	More or less good	0	0	6	2	4.95	4.804	5.097
16	Excellent	Definitely bad	Definitely bad	0	0	4	4	4.13	3.993	4.27
17	Very good	Excellent	Excellent	5	3	0	0	8.594	8.493	8.691
18	Very good	Excellent	Very good	3	5	0	0	8.215	8.104	8.32
19	Very good	Excellent	More or less good	1	5	2	0	7.367	7.239	7.494
20	Very good	Excellent	Definitely bad	0	4	2	2	5.889	5.757	6.02

9 CONCLUSION

Our research is motivated by the fact that ontological reasoning approaches cannot deal with missing or ambiguous information, which is common case in ambient, semantic web environments. In addition to that, they are not able to provide support for decision making in crucial situation. This inconsistency leads to security issues. In this work, we proposed adaptive system to deal with vagueness through Type 2 rough context ontology in terms of *upper, lower, tightupper, tightlower, looseupper, looselower approximations.* Our ontology overcomes vagueness and it takes others aspects such as acquisition, adaptation, discovering, prediction and etc. in context aware applications. The proposed model is semantic and adaptive middleware platform, where entities have intelligent characters and can adjust themselves adaptively according to their changes to data consistency and integrity with high performance level.

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