Flexible, Dynamic and Improved Intelligent Tutoring Systems (ITSs)

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Abstract— Now day's online learning is very common and fast growing industries worldwide in different institutions. This paper presents novel approach for optimized ITSs. We proposed methodology and algorithms for designing efficient deployment, interoperability and ontology extraction of ITSs framework. There are three main contributions in this research work. First, proposed an efficient open framework for ITSs which can solves the limitations related to interoperability issues. Proposed solution is not requiring the resources like databases; hence the restriction on interoperability learning objects is removed. This approach overcomes the limitations of external resources dependencies. Secondly, proposed method for automatic ontology generation using fuzzy ontology algorithm in order save efforts of end users those are required to analyze the large number of messages in ITS of big universities or organizations. Finally, proposed the improved automatic fuzzy ontology extraction method by using relevance feedback technique. In this paper, we presented the algorithms, architecture and results achieved for each contribution. The results are compared with existing methods and claimed that proposed methods are efficient for ITSs.

Key words: Concept Maps, Ontology Extraction, Encryption, Decryption, Relevance Feedback, Precision, Recall, Accuracy

I. INTRODUCTION

Now a day online teaching and learning through the electronic media becomes most widely used technique all over the world to save time, cost and efforts. Learning technologies and educational systems are now part of the infrastructure in many educational institutions around the world. LMS, PLE and other types of educational platforms are now very common in our schools and universities. Unfortunately, these educational tools have been mainly used to store plain educational content [1]. This type of content (such as PDF and PPT) cannot provide the high quality educational assistance that technology can. On the other hand, adaptive and personalized educational systems can provide very high quality educational assistance. For instance, ITSs are adaptive educational tools that offer direct personalized instruction and feedback to students (using artificial intelligence techniques, cognitive psychology and learning sciences). ITS have been used in several domains, from middle school math and physics, to programming languages and military applications. Many experiments have proved that ITS can be beneficial to learning. However, their popularity outside the academia is relatively low. Some of the main reasons for the reduced attractiveness of ITSs include: 1) the intrinsic complexity of their development process; 2) the impossibility of loading them in different platforms; 3) the extra effort necessary to make them available over the Web [2]. To address some of the limitations mentioned above, number of studies recently proposed with the prototype for making ITS more viable to educational institutions. Since tutors are not interoperable, they end up not being shared and, thus, are not accessible to many users. This limitation is significant because tutoring systems can be very effective. Additionally, given that ITSs require a substantial amount of time and resources to be implemented, it is desirable that they could be shared, used by many students, accessed from many places, and loaded onto different platforms.

On the other hand, one of the hottest R&D topics in recent years in the AI (Artificial Intelligent) community, as well as in the Internet community, is the Semantic Web. As the mostly all the e-learning interfaces are web-based, hence it is important to have efficient approaches for text retrieval and representation at both teachers and students ends. It is about making the Web more understandable by machines. It is also about building an appropriate infrastructure for intelligent agents to run around the Web performing complex actions for their users. In order to do that, agents must retrieve and manipulate pertinent information, which requires seamless agent integration with the Web and taking full advantage of the existing infrastructure (such as message sending, security, authentication, directory services, and application service frameworks) [3] [4]. Furthermore, Semantic Web is about explicitly declaring the knowledge embedded in many Web-based applications, integrating information in an intelligent way, providing semantic-based access to the Internet, and extracting information from texts. Ultimately, Semantic Web is about how to implement reliable, large-scale interoperation of Web services, to make such services computer interpretable to create a Web of machine-understandable and interoperable services that intelligent agents can discover, execute, and compose automatically. The problem is that the Web is huge, but not smart enough to easily integrate all of those numerous pieces of information from the Web that a user really needs. Such integration at a high, User-oriented level is desirable in nearly all uses of the Web. Today, most Web information is represented in natural-language; however, our computers cannot understand and interpret its meaning. Humans themselves can process only a tiny fraction of information available on the Web, and would benefit enormously if they could turn to machines for help in processing and analysing the Web contents. Unfortunately, the Web was built for human consumption, not for machine consumption - although everything on the Web is machine-readable, it is not machine-understandable [5]. We need the Semantic Web to express information in a precise, machine-interpretable form, ready for software agents to process, share, and reuse it, as well as to understand what the terms describing the data mean. That would enable Web-based applications to interoperate both on the syntactic and semantic level. The explicit representation of the semantics of data, accompanied with domain theories (that is, ontology), will enable a Web that provides a qualitatively new level of service - for example, intelligent search engines, information brokers, and information filters. There is research on important issues related to the development of the Semantic Web, and their implications for Web-based teaching and learning. It describes what it means precisely to create, to find, and to use educational resources on the Semantic Web pages, as opposed to doing it on today's Web. The ontology extraction is widely studied methodology for information extraction in ITSs. Ontology extraction methods are generally suffering from the accuracy of information extraction and complexity of text representation [6] [7].

Next, the information sharing over the ITS's standards is important to educational organizations such as questions, examination details, shared documents, admin communications etc. Most of existing standards did not bothering about providing the security to such methods along with dynamic deployment and efficient ontology extraction. This work first presents the framework for implementing interoperable tutors with the support of standards with cryptography efficient algorithms for information security [8]. This method target the sharable content object reference model (SCORM) e-learning standards. This method allows implementing web-based ITSs as learning objects (LOs) and using a novel structural design that focuses on supporting the essential features of intelligent tutors, the inner loop and the outer loop. Then we designed the novel ontology extraction methods for data extraction and representation on web pages [9]. In section II, the related works on ITS systems are discussed. In section III, the proposed framework and algorithms for each one are discussed. In section IV, the results are discussed. In section V, conclusion and future work presented.

II. RELATED WORKS

A. ITS

The tutoring system architecture is consisting of four main components. The first model is instructional model for ITSs is depends on participating students in activities related to problem solving via the user interaction. The next model is domain module which is nothing but the expert system which is used to evaluate the student actions. Another model called student model which is used to store the student information that ITS have. Finally the last model pedagogical model gives the instructional interventions as well as feedback to the apprentices. Such traditional types of ITSs are widely acceptable to many communities. But the latest papers stress procedure on structure [1], [2], [3], discussing about ITSs which are having two loops such as inner loop and outer loop. The tasks of inner loop are giving personalized feedback, problem solving support to end users or students, hints etc. This loop also used to access the competence of students and store it into the student model. The information which obtained about the student is used by outer loop for the task selection.

In [4], [5], and [6] presented methods for interoperable and adaptive technique for online learning systems. These methods resulted into better approach for learning. The GRAPPLE project introduced is based on combining LMSs with adaptive learning conditions by building the generic adaptive webserver architecture. This gives the browser dependent authoring systems as well as distributed framework for user modelling. Web based adaptive education tool is created and supported by GRAPPLE. This also supports different types of adaptation like link, content, presentation etc. In addition to this, GRAPPLE has ability to support different kinds of under model knowledge.

In [7], authors Gustavo Soares Santos, Joaquim Jorge introduced the approach for discussing problems and challenges in ITSs. The framework introduced by authors is solves the problem of interoperability and compatibility. In this paper we considered this work as our base work for further research and extension. Extension related part is out of scope of this paper, rather aim of this paper is to describe the current ITSs problem and its current solution.

B. Ontology Extraction

In [8], another research work exploring the ideas of automatically extracting ontologies from teaching documents although the algorithmic details were not illustrated. Previous work had also employed the Term Frequency Inverse Document Frequency (TFIDF) heuristic developed from the field of IR to extract prominent concepts from electronic messages generated in e-Learning [9]. A knowledge density score was developed based on the TFIDF term weighting formula to assess the extent of contribution to online knowledge sharing by individuals.

In [10], author introduced the ontology mining technique to extract patterns representing users' information needs. The ontology mining method consists of two parts: the top backbone and the base backbone. The former represents the relations between compound classes of the ontology. The latter indicates the linkage between primitive classes and compound classes. The Dempster-Shafer theory of evidence model was applied to extract the relations among classes. The strength of the ontology mining method is that it can effectively synthesize taxonomic relations and non-taxonomic relation in a single ontology model. In addition, a novel method was proposed to capture the evolving patterns in order to refine the initially discovered ontology. Finally, a formal model was developed to assess the relevance of the discovered ontology with respect to the user's information needs.

In [11], author Sanderson and Croft proposed a document-based subsumption induction method to automatically derive a hierarchy of terms from a corpus. In particular, the subsumption relations among terms are developed based on the co-occurrence of terms in the documents of a corpus. Even though the idea is interesting, the computational method may not be robust enough to deal with taxonomy extraction tasks in general.

In [12], author proposed the ontology discovery approach to improve domain ontologies by mining the hidden semantics from text. The learning approach is based on self-organizing map (SOM). The words occurring in free-form text documents from the application domain are clustered according to their semantic similarity based on statistical context analysis. A word is described by words that appear within a fix-sized context window, semantic relations of words are then extracted and represented in the self-organizing map. It is argued that such an approach is suitable for finding new concepts and relations to be added to the associative network. The SOM approach was illustrated with reference to the tourism domain and a field test based on the largest.

In [13], author maintained that future ITSs must be built upon ontologies and proposed building the system using three level ontologies. Level one and two ontologies should define basic terms and definitions about those terms, whereas the ontology on level three should work with software modules. Later, they have built an instructional theory-aware system [13]. The basis of the system is an ontology that contains all the instructional theories. The creator of the course has to make relations between predefined Learning Objects and the theories of the ontology. This way, the tutoring system triggers events, which depending on the theories previously selected, make different actions to happen. The advantage of this system is the possibility of merging different instructional theories. The course creator can define different WAYs. This is, different ways to make the learner acquire knowledge. The disadvantages are that the ontology must be maintained by an expert and that the domain model of the course is not reusable.

In [14], author presents a system where ontologies are the core of the system. The system is based in four ontologies: the Domain Ontology, where the characteristics of the domain knowledge are provided, the Student model ontology, the Pedagogical model ontology and the Interaction ontology.

III. METHODOLOGY

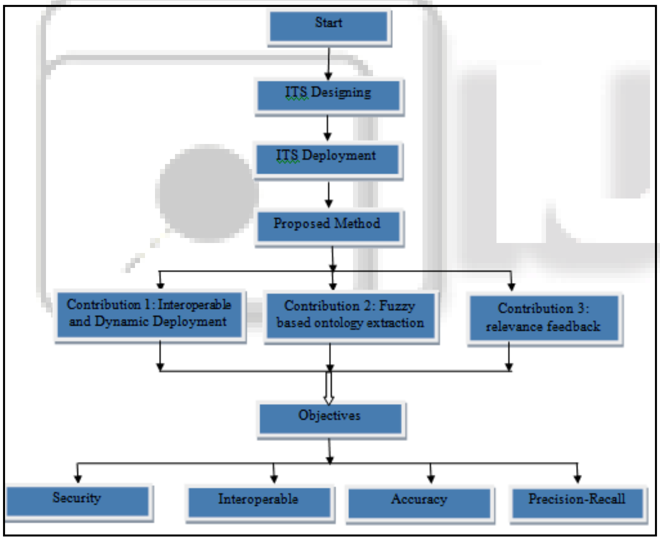

Fig. 1: Proposed System Design

Figure 1 is showing the framework for proposed framework. As showing in figure, first approach for the development of interoperable ITSs using e-learning standards is proposed. This proposed method is based on the development of atomic tutoring systems that are grouped to create molecular tutors, covering the curriculum of courses. In addition, our approach focuses on assuring what defines a tutor in terms of behavior and functionalities (inner loops and outer loops). In contrast to other approaches, this proposed method does not require extending standards with non-standardized peripheral systems or databases. In addition, we are using the SCORM Tin Can API; this is new version of SCORM (Tin Can is promising more powerful ways of storing data about the users and groups of users) which will further improve the performance of our ITSs. Also, the information security is provided with this contribution. To satisfy the need of efficient information discovery, we further contributed with automated tool for concept map generation in order to help teachers to analyse as well as visualize important information composed in huge number of online messages posted on their walls via online chatting's, blogs, emails etc. This can solves the problem of large data overload on instructors and learners and delivers the efficient and adaptive ITSs. The earlier methods discussed in related work section claiming that in knowledge intensive domains, the problem solving of individuals can be predicted through analysis of content and structural characteristics of concept map designed by individual. Finally, we proposed the second variant of ontology extraction method with goal of user reviews consideration. We proposed our automated method for concept map generation by using the concept of automated relevance explicit feedback on knowledge discovering process. This can approach can improve the performance of knowledge discovering by keeping the logs user feedbacks while extracting the more accurate important information's during online sessions.

A. *Security Methods*

In first contribution, along with interoperable ITSs design, we proposed secure data communication using below encryption and decryption algorithms.

1) *Algorithm for Encryption*

- Step 1: Receive Input data from source or intermediate node with *n* size bits
- Step 2: Apply initial permutation by dividing input data equally with each of size as

  L0 = n/2;
  R0 = n/2;

  [Note: L for left side and R for right side]
- Step 3: Apply second level permutation using below equations

  LL0 = L0/2;
  LR0 = L0/2;
  RL0 = R0/2;
  RR0 = R0/2;
- Step 4: Apply DES with Key on all four parts individually

  Key =Key size used here for DES is 128 bits
  LL1 = DES (LL0, key);
  LR1 = DES (LR0, key);
  RL1 = DES (RL0, key);
  RR1 = DES (RR0, key);
- Step 5: Combine Data at Second Level after DES

  fL0 = LL1 + LR1;
  fR0 = RL1 + RR1;
- Step 6: XOR first level data

  Out = (fL0 XOR fR0);
- Step 7: Apply AES on output of XOR

  R1 = AES (Out, key);
- Step 8: L1 = fR0
- Step 9: Generate Encrypted Data

  Encrypt_d = R1+L1

2) *Algorithm for Decryption*

- Step 1: Receiving input encrypted data from previous node in path.
- Step 2: Apply initial permutation by dividing input data equally with each of size as

  L0 = n/2;
  R0 = n/2;

[Note: L for left side and R for right side]

- Step 3: Apply AES on R0
  Key = Key size used here for DES is 128 bits
  R1 = AES (R0, key);
- Step 4: XOR R1 with L0
  OutR = (R1 XOR L0);
- Step 5: Generate left output using R0
  OutL = R0;
- Step 6: First Level Partition
  LL0 = OutL/2;
  LR0 = OutL/2;
  RR0 = OutR/2;
  RL0 = OutR/2;
- Step 7: Apply DES with Key on all four parts individually
  Key size used here for DES is 128 bits
  LL1 = DES (LL0, key);
  LR1 = DES (LR0, key);
  RL1 = DES (RL0, key);
  RR1 = DES (RR0, key);
- Step 8: Combine Decrypted Data
  L0 = (LL1+LR1);
  R0 = (RL1+RR1);
- Step 9: Generate Decrypted Data
  Decrypt_d = L0+R0;

B. *Ontology Extraction*

This section shows the algorithm combined with contribution II and III for efficient ontology extraction.

Below is algorithm for proposed approach.

1) *Algorithm 1: IOntExtraction (CT, TR, OTE)*

- Input: corpus CT and vector of threshold values TR
- Output: light weight fuzzy domain ontology *Ont*
- Main functionality:

1) Step 1: Ont = {}
2) Step 2: For each document d ∈ CT Do
   - Construct text windows ω ∈ d
   - Remove stop words sω from ω
   - Perform POS tagging for each term ti∈ ω
   - Apply Porter stemming to each term t_i
   - Filter specific linguistic patterns
   - Accumulate the frequency for t_i∈ ω and the Joint frequency for any pair t_i , t_j ∈ ω
   - IF lower ≤ Freq(t_i) ≤upper, A = A ∪ t_i
3) Step 3: For each term t_i ∈ A Do
   - Compute its context vector C_i using BMI, MI, JA, CP, KL, ECH, or NGD
   - C = C ∪ C_i
4) Step 4: For each C_i ∈ C Do /* Concept Pruning - α-cut */
   IF ∃t_i ∈ C_i : $\mu C_i(t_i) < \zeta$
   THEN C = C − C_i
5) Step 5: ∀C_i ∈: Compute Rel(C_i, CT_j)
6) Step 6: IF Rel(C_i, CT_j) < ϖ /* Concept Filtering */
7) Step 7: THEN C = C − C_i
8) Step 8: Perform Dimensionality Reduction SVD
9) Step 9: For each pair of concepts C_i , C_j ∈ C Do
   - Compute the taxonomy relation r(C_i , C_j) using Spec(C_i , C_j)
   - IF $\mu R_{cc}(C_i , C_j) > \lambda$, R_{cc} = r(C_i , C_j)
10) Step 10: For each r(C_i , C_j) ∈ R Do /* Taxonomy Pruning */
    - IF $\mu R_{cc}(C_i , C_j) < \mu R_{cc}(C_i , C_j)$
    - THEN $R_{cc} = R_{cc}$ − r (C_i , C_j)
    - IF ∃ P (C_i →C_x, . . . , C_y → C_j)
    - AND μ $R_{cc}(C_i ,C_j) \leq$ min ({$\mu R_{cc}(C_i , C_x)$, $\mu R_{cc} (C_x, C_y)$, . . . , $\mu R_{cc}(C_y , C_j)$})
    - THEN $R_{cc} = R_{cc}$ − r (C_i , C_j)
11) Step 10: Output ont
12) Step 11: If user satisfied, then stop
13) Step 12: else, generate user feedback
14) Step 13: generate logs
15) Step 14: go to step 9.
16) Step 15: filtered results of Ontology.

In this algorithm step 1-10 are related to contribution second and steps 11 to 15 related to contribution third.

IV. RESULTS AND DISCUSSION

The implementation of this work is done using DOTNET platform and SCORM APIs to support the interoperability of intelligent mentors. Below diagrams are showing the design use cases for admin, student and mentor showing the implementation plan for ITSs.

A. *Contribution 1 Results*

Below table 1 is showing the encryption time required for user login and registration between existing AES, DES methods and proposed Hybrid-AES-DES methods.

	AES	DES	Proposed
Teacher Login	0.074	0.081	0.0675
Student Login	0.073	0.078	0.0643
Teacher Reg.	0.133	0.139	0.118
Student Reg.	0.126	0.129	0.102

Table 1: Performance Analysis of Encryption Time

Above table 1 is showing the performance analysis of encryption time. From the results, it is showing the proposed cryptography method taking less time for processing the encryption to secure their personal information's such as userid and password. Proposed method outperformed the existing methods.

B. *Contribution 2 Results*

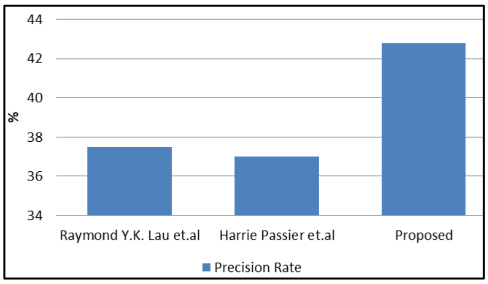

Fig. 2: Precision Rate Analysis

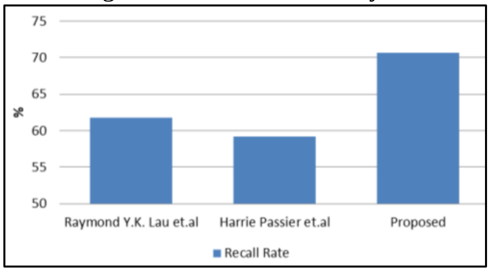

Fig. 3: Recall Rate Analysis

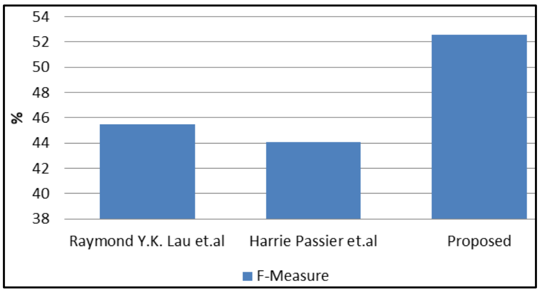

Fig. 4: F-Measure Analysis

Above graphs are showing the comparative analysis between existing authors methods for ontology extraction with proposed technique without relevance feedback. Graphs are showing that proposed ontology extraction technique is more accurate as compared to existing works of ontology extraction in e-learning framework.

C. Contribution 3 Results

Finally in this contribution we modified our second contribution then compared its performance against second contribution.

We have evaluated the existing and proposed method performances for 10 different test topics names for ontology extraction in terms of three performance metrics such as recall, precision and F-measure. Table 2 is showing the results for first method of ontology generation. Whereas table 3 is showing the results for modified and proposed method.

Topic Number	Recall	Precision	F-Measure
Topic 1	76.3 %	47.4 %	58.5 %
Topic 2	73.5 %	56.5 %	64.0 %
Topic 3	69.1%	61.5 %	65.1 %
Topic 4	76.5 %	40.9 %	53.3 %
Topic 5	68.3 %	41.4 %	52.1 %
Topic 6	80 %	33 %	47 %
Topic 7	68.05 %	27.3 %	39.4 %
Topic 8	73.6 %	31.5 %	44. %
Topic 9	62.7 %	37. 3 %	46. %
Topic 10	75.4 %	52.7 %	62 %
AVG	70.7 %	42.8 %	%

Table 2: Performance Analysis Second Contribution ontology extraction algorithm

Topic Number	Recall	Precision	F-Measure
Topic 1	86.3 %	67.4 %	76.6 %
Topic 2	80.5 %	61.5 %	71.0 %
Topic 3	75.44 %	67.45 %	71.44 %
Topic 4	79.6 %	53.5 %	66.5 %
Topic 5	70.8 %	55.9 %	63.35 %
Topic 6	81.5 %	63.9 %	72.7 %
Topic 7	73.4 %	57.5 %	65.45 %
Topic 8	75.9 %	51.5 %	63.7 %
Topic 9	66.4 %	56. 3 %	61.35 %
Topic 10	77.7 %	59.8 %	68.75 %
AVG	76.73 %	%	67.88 %

Table 2: Performance Analysis proposed ontology extraction algorithm

Table 2 showing the results of using our fuzzy based automatic ontology extraction in which overall accuracy is around 52.6 %. Table 2 is showing the modified method based performance results in which accuracy is showing around 67.88 % which is increased by around 13 % as compared to our second contribution method.

V. CONCLUSION AND FUTURE WORK

In this paper, first objective was to present automatic, flexible and dynamic framework for using the ITSs at any platform by anyone with needing any addition resources. The problem is solved by using concepts of interoperable mentor system with help of SCORM educational standard. In our first objective we have designed two algorithms one for designing ITSs components and other is for efficient cryptography method. A result for encryption time is showing that proposed work is outperforming the existing cryptography methods. Secondly we introduced the new technique for ontology extraction in ITSs frameworks using fuzzy method and relevance feedback method. We have used the explicit user feedback method in which end users of ITS will provide the feedbacks on extracted ontologies on their walls during live sessions. These feedbacks are recorded into the log files which are further used to refine the results and generate more accurate and related ontology information. Practical results showing that proposed method showing improved accuracy by 13 % as compared to existing methods. For future work we suggest evaluate the performance of proposed approach under real time systems.

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