Intelligent Steganalytic System: Application on Natural Language Environment

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Abstract: - This paper presents a consolidated view of the computational intelligence used in the natural language steganalysis. In order to understand the human intelligence on natural language, four major computational intelligence methods have been identified. They are bayesian, fuzzy logic, neural network, and genetic algorithm. This paper also presents a measurement tool to measure the natural language intelligent system properties based on steganalysis objectives. It can be learned that the more suitable intelligent systems to be applied in steganalysis domain properties are: neural network, genetic algorithm and fuzzy logic.

Key-Words: - Computational Intelligence, Steganalysis, Intelligent Steganalytic System, Natural Language Steganalysis

1 Introduction

Mankind demonstrates his intelligence by communicating effectively (through text, pictures, verbal expressions, or other medium), that is by acquiring new knowledge through experience, and then demonstrating what they have learned by communicating. Effective communication requires skills both in analysis of messages and in synthesis of messages. Besides that, the ability to learn or adapt one's behaviour to new situations is considered by many to be a vital component of intelligence. Indeed understanding a message also requires intelligence [1]. Therefore, from analysis point of view, an intelligent system is needed to understand the human intelligence especially on natural language understanding. Thus, serious efforts has been done to develop computerized systems for natural language understanding, and machine translation have taken place for more than half a century. However, the more general the domain, the more difficult it is to reach high quality translation. The same applies to natural language understanding. All systems need to deal with problems like ambiguity, lack of semantic coverage and pragmatic insight. With the progress of computation ability, various methods concerning computational intelligence have been successfully proposed [2]. This is because a fundamental goal of computational intelligence is the manipulation of natural language (NL's) using the tools of computing science. One of such analyses found that a supervised learning based approach using computational intelligence [3] can be implemented to solve the natural language problem.

Computational intelligence is the study of the system design that acts intelligently in order to understand the principles that make intelligent behaviour possible, which involve iterative development or learning. Computational intelligence is also known as Soft Computing (SC) which is a very young discipline compared with other disciplines that have been studying intelligence much longer such as philosophy, neurobiology, evolutionary biology, and psychology. There are four major methods of computational intelligence which are bayesian, fuzzy logic, neural network, and genetic algorithm. IEEE Computational Intelligence Society has also defined subjects in computational intelligence include fuzzy systems, neural networks and evolutionary computation (genetic algorithms and swarm intelligence). One of the latest studies in computational intelligence is on steganalysis environment. The implementation of computational intelligence and their hybrid methods on steganalysis environment are collectively referred to as *Intelligent Steganalytic Systems* (ISS) as shown in Fig.1. ISS are becoming increasingly distributed in terms of both their applications and implementations when comes to

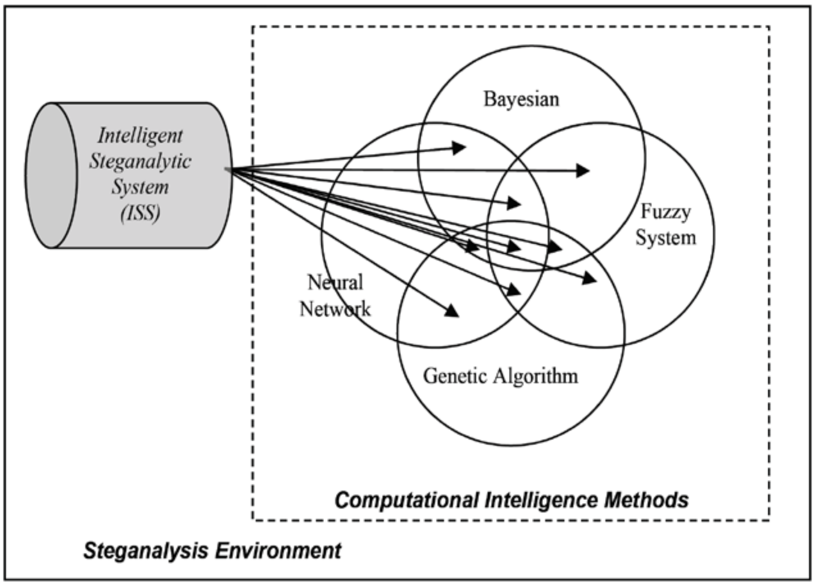

Fig.1. Synthesis of computational intelligence methods on steganalysis environment [4]

utilizing computational intelligence methods. There are three (3) main reasons for creating ISS which are integration of different technique enhancement, multiplicity of application tasks, and realizing multifunctionality. Most of their results have proven that the application of ISS has given a great influence on steganalysis performance. This paper is organized as follows.

Section 2 contains the implementation of the computational intelligence on natural language environment. Section 3 deals with the measurement of intelligent system properties, which is based on steganalysis objectives on natural language. Concluding remarks are given in Section 4.

2 Computational Intelligence Approach on Natural Language

There are numerous methods of computational intelligence that have been identified and widely used on natural language in order to understand the human intelligence such as bayesian, fuzzy logic, neural network, and genetic algorithm. This section will discuss the mentioned computational intelligence methods that have been used on natural language.

a. Bayesian - Approach for Text Classification

Bayesian networks are popular within the community of uncertainty in computational intelligence. A Bayesian network is a graphical representation that depicts conditional independence among random variables in the domain and encodes the joint probability distribution. With a network at hand, probabilistic inference can be performed to predict the outcome of some variables based on the observations of others. In light of this, Bayesian networks are widely used in diagnostic and classification systems [5].

Computationally, Bayesian networks provide an efficient way to represent relationships between attributes and allow reasonably fast inference of probabilities. Learning and reasoning are the main tasks of analyzing Bayesian networks [6]. The learning process through Bayesian networks has several advantages [7] which are easy to encode knowledge of an expert in a Bayesian network, and such knowledge can be used to improve learning efficiency and accuracy. Most of the text or document classification methods in Bayesian networks are based on the classical pattern recognition approaches. Generally, there are five Bayesian classifiers for document classification which are Naïve Bayes, Tree-Augmented Naïve Bayes (TAN), Compound terms [8], Discriminative Function, and The Bayesian Spanning Tree [9]. Tree Augmented Naive Bayes network is an effective and a stable classifier [10] which has demonstrated a stronger performance compared to the other Bayesian classification methods [11].

b. Fuzzy - Approach for Text Representation

Up to now, research on fuzzy systems has gone into two main directions. The first one is considerably formal, and generalizes non-deterministic systems such as fuzzy machine models and fuzzy formal grammars, fuzzy neural networks, fuzzy algorithms and fuzzy programs. Meanwhile, the other is the linguistic approach to fuzzy systems, which is closely related to the theory of approximate reasoning, in which a fuzzy model is viewed as a linguistic description by virtue of fuzzy logic propositions. It may be more directly applicable to natural language [12]. Meanwhile, Halliday [13] has concerned a fuzzy grammatics with theory of language, in the context of natural language as a metalanguage for intelligent computing. Among the main issues in computer environment, data representation is the transformation of natural language propositions into a formal computer manipulable language. The most established paradigm of the data representation in fuzzy logic is the paradigm of computing with words through Generalized Constraint Language-GCL [14] as shown in Fig.2.

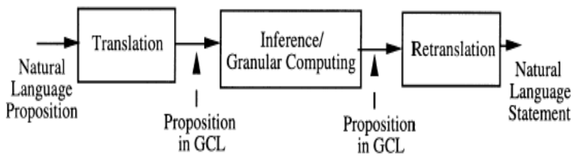

Fig.2. Process of Computing with Words [15]

Moreover, quantification is an important topic in knowledge representation and reasoning. Fuzzy quantifiers are, in principle, a powerful method for combining information [16]. The importance of fuzzy quantifiers in natural language has been pointed out on many occasions [17 - 18]. On the other hand, having adequate tools for the representation of natural language quantifiers is useful for an important number of applications such as expert systems, decision making and database systems.

c. Neural Network - Approach for Text Processing

Neural networks are being applied to a wide variety of automation problems including adaptive control, optimization, medical diagnosis, decision making, as well as information and signal processing, including speech processing. While neural networks are good at recognizing patterns, they are not good at explaining how they reach to their decisions.

Thus, selecting the weights of the decision is considered as a key issue in the use of neural networks. Neural networks can model complex non-linear relationships, and approximate any measurable function. They are also very good at classification of phenomena into preselected categories used in the training process [19]. The most difficult part of any neural network training problem is defining the proper training set [20].

Neural network, however, can capture the implicit information in the training data since they can model both the negative as well as the positive relationships [22]. Several researchers have successfully used neural networks to process natural languages [23 -25]. There are several aspects on natural language which are using neural networks intensively such as partial parser [26], natural language learning [27], grammatical inference [28], NeurAlign [29], natural language translation [30], perception-based probabilistic model [31], and language modeling on large text corpora [32].

d. Genetic Algorithm - Approach for Text Optimization

Genetic algorithm is a robust search algorithm based on the mechanics of natural genetics to guide their trek through a search space, and finding increasing popularity in the field of optimization [33]. The main idea behind a genetic algorithm is the evolution of a problem's solution over many generations with each generation having a better solution than its predecessor. The language of genetic algorithm is heavily laced with biological metaphors from evolutionary literature, such as population, chromosome, crossover, cloning, mutation, genes and generations. Genetic algorithms are most appropriate for optimization type problems of the natural languages grammar. Based on the principle of "survival of the fittest", genetic algorithm can be used to learn the weights of a constraint dependency grammar from a corpus of annotated utterances.

Thus, the grammars of natural languages may be learned by using genetic algorithms that reproduce and mutate grammatical rules and part-of-speech tags, improving the quality of later generations of grammatical components [34]. Several studies have been used GA on natural language such as natural language tagging [35], Optimality Theoretic (OT) systems [36], evolving natural language grammars induction [37] and model of language structure [38].

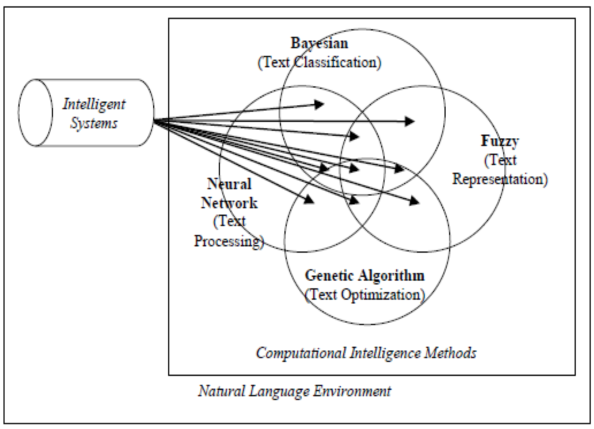

Fig.3. Intelligent System on Natural Language Environment [39]

Thus, based on the above explanation, it can be said that bayesian, neural network, fuzzy system and genetic algorithm methods are the prominent computational intelligence methods on natural language. Commonly, these methods and their hybrids are collectively referred to here as *Intelligent System (IS)* as shown in Fig.3.

3 Intelligent System Properties

Since the theory and practice of intelligent system in the process is being developed, there has been little emphasis in the literature to measure the usage of computational intelligence methods in natural language steganalysis. This measurement can be tested based on the steganalysis objectives such as security and robustness [40]. Thus, Table 1 has classified enormous research findings on several properties of intelligent systems [41 - 42] that have been identified on natural language.

Table 1: Property assessment of intelligent system properties on natural language environment

Features	Properties	Steganalysis
Fuzzy diagnosis [43]	Reasoning Under Uncertainty	Very Relevance
Bayesian Networks deal with the uncertainty problems [44]	Reasoning Under Uncertainty	Very Relevance
The GA is a robust, effective and fault-tolerant method [45]	Failure Detection	Very Relevance
Fuzzy logic is good enough, as the number of correctly detected consultations [46]	Inference	Relevance
Fuzzy-quantified have shown the effectiveness of inference method [47]	Inference	Relevance
Hierarchical neural network system is best suited for text [48]	Learning	Relevance
The recurrent network learned sentence-processing patterns perfectly [49]	Self-Learning	Relevance
Artificial neural network-based language processing has many potentials [50]	Self-Learning	Relevance
Linguistic rules can be extracted from a multilayer feedforward neural network [51]	Self-Learning	Relevance
Neural network can learn a language model [52]	Self-Learning	Relevance
Recurrent neural networks are used to classify natural language sentences [53]	Self-Learning	Relevance
Neural network language models on large amounts of text corpora [54]	Self-Learning	Relevance
Parsing natural language texts using fuzzy context free grammars [55]	Self-Learning	Relevance
Neural network can process data and efficiency of genetic algorithm is used to evolve them [56]	Adaptation and Learning	Relevance
The hybrid approach through combination of genetic algorithm and ILP [57]	Adaptation and Learning	Relevance
The genetic algorithm has been found better on search space exploration [58]	Adaptation and Learning	Relevance
The synthesis of neural network, fuzzy system and genetic algorithm [54]	Adaptation and Learning, Optimization	Very Relevance
The particle swarm optimization on feature dimension reduction [59]	Optimization	Relevance
Genetic algorithms can provide automatic configuration for NN attacking complicated tasks [60]	Self-Reconfigurabilit y	Very Relevance
Fuzzy-neural controller [61]	Setting Control Goal	Relevance
Genetic algorithms used as a fully automatic substitute tool [62]	Autonomous and Intelligence	Very Relevance
Genetic algorithm is used successfully create symbolic expressions [63]	Non-Linearity	Very Relevance
Genetic algorithms are symbolic learners [38]	Non-linearity	Very Relevance
Representation of ambiguity in fuzzy logic [64]	Operator Representation	Relevance
Fuzzy quantifiers and truth qualifiers [65]	Operator Representation	Relevance
Representation of sentences by fuzzy semantics [66]	Knowledge Representation	Very Relevance
Tree Augmented Naive Bayes network classifier is stable classifier [67]	Classification	Not Relevance
Bayesian text classification [68]	Classification	Not Relevance
Poisson naive Bayes text classification model with weight-enhancing method [69]	Classification	Not Relevance
Bayesian spanning tree for document categorization [70]	Classification	Not Relevance

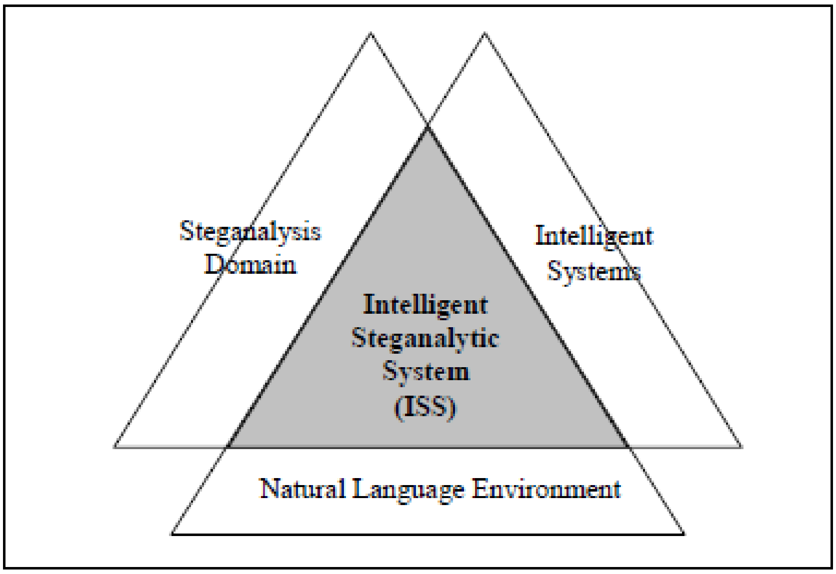

Fig.4. A building block of intelligent steganalysis system in natural language environment

It can be learned that the more suitable intelligent systems to be applied in steganalysis domain properties are: neural network, genetic algorithm and fuzzy logic. Neural network technique is more effective than previously existing techniques [71, 72, 73] and has better performance compared to Bayesian network due to its powerful learning capability in steganalysis.

Even though neural network technique is stronger on pattern recognition and learning capability, it lacks on systematic rule for feature selection. This is because neural network technique is using a heuristic trial and error process to train its classifier. Thus, the use of genetic algorithm offers a better solution to the above problems. Genetic algorithm is a good intelligent system technique in producing a systematic rule for feature selection of solution and very powerful for optimization. In addition, it has been identified as well to pass the detection of current steganalytic systems and also worked effectively on audio steganalysis and image steganalysis. As a result, neural network classifier can be trained efficiently by using the genetic algorithm. It is important to improve the efficiency of artificial neural network training and simplify the training algorithm. Several studies [74] have proven the effectiveness of the combination genetic algorithm and neural network in the dynamic environment is as good as the Dynamic Evolving Neural Fuzzy Inference System (DENFIS) which has been presented by Liu and Sung [75] (as an example of a hybrid intelligent system method).

Combination of neural network and genetic algorithm will produce good network architecture for steganalysis in order to learn and justify the hidden message in natural language. Nevertheless, such justification needs to be verified on whether the text contain hidden message or vice versa. This action can be achieved by using a fuzzy logic feature where the output of neural network/genetic algorithm or combination genetic-neural can be manipulated through fuzzy reasoning based on its membership functionality and the capability of the fuzzy explanation. Perhaps, by combining neural network, genetic algorithm and fuzzy logic, this study will attain a powerful steganalysis tool for natural language. Thus, based on the above explanation, it can be summarized that the primary constituents of ISS on natural language are including natural language environment, steganalysis domain and intelligent systems approach as shown in Fig.4. It has also identified that an ISS can be utilized on natural language steganalysis. Despite different computational intelligence methods on ISS applications that have been proposed, the possibilities of using the ISS applications for natural language are still under-utilized.

4 Conclusion

This study has analyzed and classified several computational intelligence methods such as bayesian, fuzzy, neural network, and genetic algorithm on natural language in which computational intelligence can be applied more efficiently and intelligently in steganalysis application. The primary contribution of this paper is to give a new light on steganalysis approach which in returned would contribute to natural language steganalysis. The definition of natural language steganalysis, however, needs more formalization. Hopefully, a powerful steganalysis on natural language can be achieved by using hybrid intelligent system which is the integration of computational intelligence technologies. Thus, it is expected that a good and powerful steganalysis technique will be produced in a near future through this new paradigm proposed by this paper.

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