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# Biomedical Engineering Via Computational Intelligence

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## ABSTRACT

In this paper, we will review the effect of computational intelligence in biomedical engineering. Efficacy of computational intelligence demonstrated by use of a case study in this area. Computational intelligence has found applications in many areas; among them biomedical engineering has evolved into one of the major application areas of computational intelligence. In this paper, we give a brief review of biomedical applications of computational intelligence. The effectiveness of computational intelligence for medical diagnosis is demonstrated.

**Keywords :** Computational Intelligence, Artificial Neural Network (ANN), Evolutionary Computation, Fuzzy Logic Systems, Biomedical Engineering.

## 1 Introduction

Several methodologies (or concepts) have matured in the last decade that facilitate solving problems that were previously difficult or impossible to solve. These methodologies include artificial neural networks, fuzzy systems, and evolutionary computation. Implementations and applications of these methodologies have been widely published. Recently, these new methodologies, known collectively as computational intelligence concepts, have been combined, among themselves as well as with more traditional approaches such as statistical analysis and rule-based symbolics, to solve extremely challenging problems. For example, medical diagnostic systems have been developed that include Bayesian, neural network, and rule- based diagnostic modules, genetic algorithm based explanation facilities, and expert system shells. All of these components work together in a "seamless" way that is transparent to the user, and system performance significantly exceeds that which is available with any single approach [1].
Biomedical Engineering is an interdisciplinary domain, which links many disciplines such as engineering, medicine, biology, physics, psychology, etc (Wolff 1970). This rapidly growing field must meet the needs of industrial, clinical, and scientific research communities. It involves the application of state-of-the-art technology to the creation of methodologies and devices for human welfare and for better understanding of human biological processes. Artificial neural network is one of the techniques that can be utilized in these applications [2].

These concepts are being combined in ways that sometimes makes categorizing them difficult. For example, computational intelligence systems, a few of which are mentioned in this paper, have been developed that incorporate neural network, fuzzy logic and evolutionary computation paradigms. These systems are able to quickly solve classification and clustering problems that are extremely time consuming using other techniques. It is important to note that computational intelligence paradigms are capable of being applied, in many instances, by "domain experts" rather than only by computer scientists. This means that biomedical engineers, for example, can solve problems in biomedical engineering without relying on outside computer science expertise such as is typically required to build knowledge bases for classical expert systems. It is also important to note that computational intelligence systems are usually capable of yielding results, at least at a system prototype level, in a relatively short time. For example, the implementation of a conventional expert system often takes one to three years, and requires the active participation of a "knowledge engineer" to build the knowledge and rule bases. Computational intelligence system solutions can often be prototyped in a few weeks to a few months, and are usually implemented using available engineering and computational resources [1].

This paper is organized as follows: In Section 2 we explain computational intelligence in general. Section 3 demonstrates applications of computational intelligence in biomedical engineering. The efficacies of computational intelligence are showed by use of a case study in this area. Finally, conclusions form the last section.

## 2 Computational Intelligence

In order to facilitate the discussion of computational intelligence applications, definitions of key terms related to computational intelligence and its main constituent methodologies (neural networks, evolutionary computation, and fuzzy logic) are presented below [1].

An artificial neural network (ANN) is an analysis paradigm that is very roughly modeled after the massively parallel structure of the brain. It simulates a highly interconnected, parallel computational structure with many relatively simple individual processing elements (PES). A neural network tool (NNT) is the implementation of an artificial neural network in software, hardware, or a combination of the two. The somewhat more abstract notion of a neural network paradigm, such as back-propagation, is usually referred to as an ANN, while a specific implementation is often called an NNT. The distinction, however, is somewhat blurred, and the terms ANN and NNT are sometimes be used interchangeably. Fuzziness refers to non-statistical imprecision and vagueness in information and data. Most concepts dealt with or described in the "real world" are fuzzy. For example, a statement, "It is kind of foggy outside now, but it should be fairly sunny before too long," is an example of a statement that incorporates three fuzzy concepts: "kind of," "fairly," and "before too long." Fuzzy sets model the properties of imprecision, approximation or vagueness. In conventional logic, known as crisp logic, an element either is or is not a member of a set. It can be said, therefore, that each element has a membership value of either 1 or 0 in the set. In a fuzzy set, fuzzy membership values reflects the membership extents (or grades) of the elements in the set. A membership function is the basic idea in fuzzy set theory; and a fuzzy membership function is identical to a fuzzy set. Fuzzy logic is the logic of "approximate reasoning". Fuzzy logic comprises operations on fuzzy sets including equality, containment, complementation, intersection and union, and is a generalization of conventional (two-valued, or "crisp") logic. Evolutionary computation comprises machine learning optimization and classification paradigms roughly based on mechanisms of evolution such as biological genetics and natural selection. The evolutionary computation field includes genetic algorithms, evolutionary programming, genetic programming, evolution strategies, and particle swarm optimization. Most widely used in applications are genetic algorithms. Genetic algorithms are search algorithms that incorporate natural evolution mechanisms including crossover, mutation and survival of the fittest. Genetic algorithm paradigms work on populations of individuals, rather than on single data points or vectors. They are more often used for optimization, but also for classification. Evolutionary programming algorithms are similar to genetic algorithms, but do not incorporate crossover. Rather, they rely on survival of the fittest and mutation. Particle swarm optimization involves "flying" candidate solutions (population members) through hyperspace, and stochastically accelerating each one toward its previous best position (the position that resulted in the best fitness) and the population's global best previous position [1].

Computational intelligence is a methodology involving computing that exhibits an ability to learn and/or to deal with new situations, such that the system is perceived to possess one or more attributes of reason, such as generalization, discovery, association and abstraction. The concept of adaptation is central to computational intelligence, and gives rise to another definition: computational intelligence comprises practical adaptation concepts, paradigms, algorithms, and implementations that enable or facilitate appropriate actions (intelligent behavior) in complex and changing environments. Adaptation seems to be the most appropriate term for what computational intelligence systems do. It may not be too far-fetched to say that computational intelligence and adaptation are synonymous [1].

## 3 Applications of Computational Intelligence in Biomedical Engineering

Biomedical engineering has become one of the major applications of computational intelligence, which is partially due to the high complexity and nonlinearity of the problems in the area, When encountering a problem, it's unnecessary to consider using computational intelligence techniques at first. First, try to use some traditional approaches to solve the problem. If it is impossible or at least very difficult to solve the problem using traditional approaches, then try to think about applying computational intelligence techniques. The point is to always consider computational intelligence techniques as second best choices [3].

Among computational intelligence tools, artificial neural networks have been applied most in the biomedical engineering area. In [4], Eberhart and Brandmaier reported approximately 200 publications of artificial neural networks' applications in biomedical engineering were found in the literature for 1993-1994 period only. A selected bibliography is listed in their paper [4].

Most successful medical applications of artificial neural networks have employed back-propagation neural networks, thanks to their characteristic of being universal approximators. A three-layer back-propagation network can theoretically approximate any function, which makes back- propagation networks well suited for applications involving classification, detection, and diagnosis problems. Actually, until now these three areas comprised the largest portion of medical applications of computational intelligence [3].

Hiraiwa, et al. [5], used feed-forward neural networks for EEG topography recognition. Jansen [6] applied neural networks to detect K-complexes in EEGs, which are relatively large waves with a duration of between 500 and 1500 msec often seen during sleep stage 2. Wilson, et al. [7], used a patient-independent neural network to detect epileptiform spikes in the EEG. Eberhart, et al. [8], used a neural network for EEG waveform classification.

Cios, et al. [9], used neural networks to detect cardiac diseases from echocardiographic images. Barro, et al. [10], used an adaptive neural network to classify multichannel ECG patterns.

Holdaway, et al. [11], used neural networks for the classification of somatosensory evoked potentials recorded from patients with severe head injuries. Gils, et al. [12], used artificial neural networks for the classification of ICU patient states. Goodenday, et al. [l3], used an image-recognition neural network to identify coronary stenosis. KOCUT, et al. [14], used artificial neural networks to select wavelet features that are available to another neural network classification systems which provide most discrimination information, and then applied these selected features to the neural classification system for breast cancer diagnosis. Kaufman, et al. [15], applied a back-propagation neural network to bone fracture healing assessment.

Similar to artificial neural networks, fuzzy systems are also universal approximators, and therefore have found many classification, detection, and diagnosis applications in biomedical engineering.

Watanabe, et al. [16], applied fuzzy discrimination analysis approaches for diagnosis of valvular heart disease and achieved a rate of true positive diagnosis of 81% while maintaining a rate of false positive diagnosis at the low level of 10%.

Smith and Arabshahi [17] developed a fuzzy decision system for ultrasonic prenatal examination. This system is helpful in reducing cost, minimizing exposure of the fetus to ultrasonic radiation, and providing a uniform examination and interpretation of the results.

Waschek, et al. [18], developed a fuzzy system to assist the radiotherapist in the process of target volume definition for three-dimensional radiotherapy of cancer patients so as to increase the diagnostic accuracy.

Stegmaier, et al. [19], developed a fuzzy system for cough detection in mechanically ventilated patients.

In addition to classification, detection and diagnosis, fuzzy systems have also been applied in biomedical engineering as controllers. Control systems are the main application area of fuzzy systems.

Meier, et al. [20], used a fuzzy system to control the depth of anesthesia with isoflurne during surgery. Linkenst, et al. [21], developed a hierarchical fuzzy-based support system for anaesthesia monitoring and control.

Another advantage fuzzy systems have over artificial neural networks is that fuzzy systems can provide the end users with explanations about how the classifications, detections and or diagnoses are made. Artificial neural networks work as more of a black box. They provide output according to input, but don't tell why which, in some situations, makes artificial neural networks unacceptable. One way to overcome this is to utilize evolutionary computation techniques, such as genetic algorithms, particle swarm optimizers, etc., to build explanation facilities for artificial neural networks [22].

Evolutionary computation techniques are mainly employed to evolve or design better classifiers, detectors, and diagnostic systems, which can include artificial neural networks, fuzzy systems or other approaches [23]. They can also be used to select relevant and/or compact input variables from a lot of candidate input variables so as to result in a small system with better performance. For example, Trafalis [24] utilized genetic algorithms to design a neural network for breast cancer diagnosis.

In lot of other cases, a combination of several different components is better than any single one.

Zahan, et al. [25], built up a hierarchy of diagnosis cells which consist of fuzzy inference systems, neural networks, neuro-fuzzy networks arid other types of hybrid systems, and have applied this hierarchical system for myocardial ischemia diagnosis.

Rosen, et al. [26] used artificial neural networks, generalized regression networks and. C4.5 decision trees to classify 140 feature patterns extracted from fetal heart rate. This system can provide automated diagnosis of fetal outcome from cardiotocograms, which provide useful information during labor.

Lin, et aI. [27], combined genetic algorithms with cascade correlation, and applied the combination for diagnosis of delayed gastric emptying from electrogastrograms.

In addition to applications to biomedical engineering problems, computational intelligence techniques can also be used as tools for analysis and/or modeling. A group of researchers at Southeast University (personal communication) introduced a control parameter into the cellular neural network so as to control the dynamic behavior of the cellular neural network. For some settings of the parameters, the dynamic trajectory of the cellular neural network looks like the electric response activity (ERA) signal. This may imply that this kind of network is a good candidate for modeling ERA, which is an undergoing research project.

Xiao, et al. [28], have applied back-propagation neural networks to extract the spindle wave and the constant amplitude wave in the 40 Hz EEG with electromyogram noise so that these waves can be used to recognize differences in cognitive states using chaos theory.

## 4 A Case Study: Medical Diagnosis with C4.5 Rule Preceded by Artificial Neural Network Ensemble

Comprehensibility is very important for any machine learning technique to be used in computer-aided medical diagnosis. Since an artificial neural network ensemble is composed of multiple artificial neural networks, its comprehensibility is worse than that of a single artificial neural network. C4.5 Rule-PANE, which combines artificial neural network ensemble with rule induction by regarding the former as a pre-process of the latter, is proposed. At first, an artificial neural network ensemble is trained. Then, feeding the feature vectors of the original training instances to the trained ensemble and replacing the expected class labels of the original training instances with the class labels output from the ensemble generate a new training data set. Randomly generating feature vectors and combining them with their corresponding class labels output from the ensemble may also append additional training data. Finally, a specific rule induction approach, i.e. C4.5 Rule, is used to learn rules from the new training data set. Case studies on diabetes, hepatitis, and breast cancer show that C4.5 Rule-PANE could generate rules with strong generalization ability, which profits from artificial neural network ensemble, and strong comprehensibility, which profits from rule induction. Fig. 1, Fig. 2, and Fig. 3 also show that the generalization ability of C4.5 Rule-PANE can be improved further by utilizing additional training data. This observation supports our claim that the data generated by the artificial neural network ensemble may be useful in complementing the original training data set for rule induction [29].

## 5 Conclusion

In this paper, based on literature we conclude that computational intelligence has a successful effect in biomedical engineering. Computational intelligence can be applied in another

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field's of biomedical engineering such as: biomaterials, electrophysiology, biotechnology, modeling, instrumentation, rehab engineering, biomechanics, medical analysis, biosensors, prothetic, imaging, clinician, computers devices, informatics. So, you can use computational intelligence as a more powerful tool for problem solving.

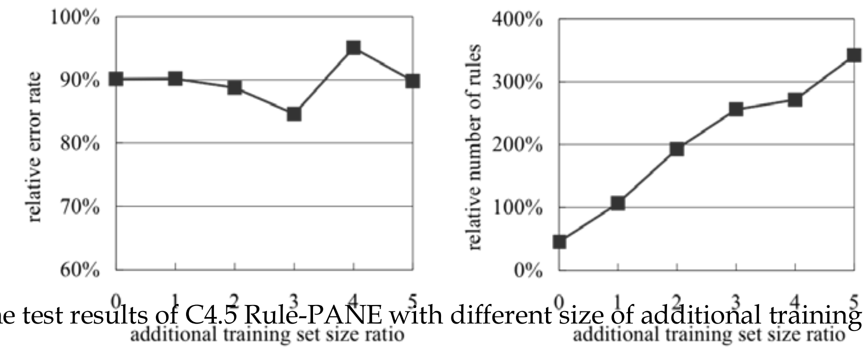


Fig. 1. The test results of C4.5 Rule-PANE with different size of additional training data set on *diabetes*

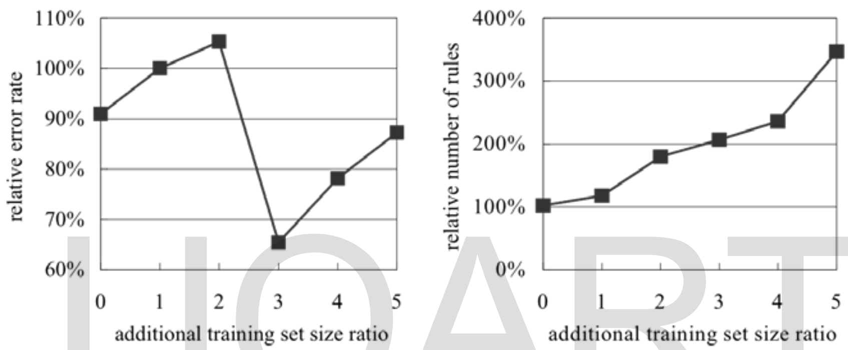




Fig. 2. The test results of C4.5 Rule-PANE with different size of additional training data set on *hepatitis*

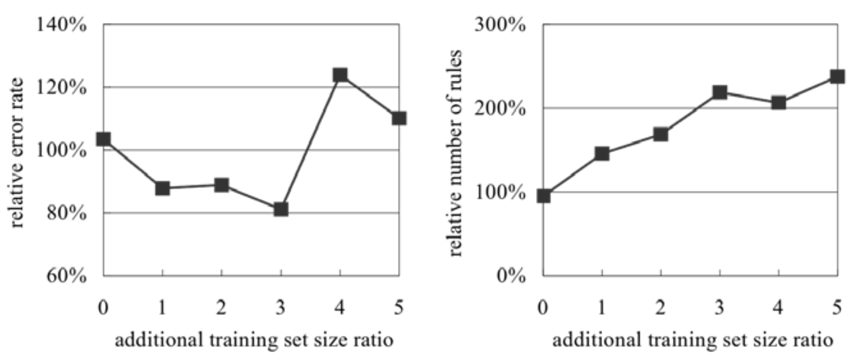


Fig. 3. The test results of C4.5 Rule-PANE with different size of additional training data set on *breast cancer*

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