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Computational Intelligence, Granular Computing and Soft Computing.

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ABSTRACT

This paper describe the theory of computational intelligence, granular computing, and soft computing. Computational Intelligence (CI) is an offshoot of artificial intelligence. Characteristics of computational intelligence (CI) systems, such as adaptation, fault tolerance, high computational speed and error resilience in the face of noisy information, fit the requirements of building a good intrusion detection model. Here we want to provide an overview of the research progress in applying CI methods to the problem of intrusion detection. Granular computing and soft computing are also two fields which are used in many intelligent machines. This paper gives to three terminology of AI that means computational intelligence, granular computing, and soft computing. What is process of that and what is use in current scenario It will also give an idea on how these computing methods are used to create intelligent agents which can possess a similar intelligence as a human of this.

Keywords: Soft computing, granular computing, computational intelligence. Probabilistic Methods, Fuzzy logic

I. INTRODUCTION

The main objective of this paper is, this paper describe the what is actual meaning of Computational intelligence, granular computing, and soft computing. And also describe the method of these terminologies like such as fuzziness and roughness, and of the neural networks theory and evolutionary computing on computing systems development. this methods for solving complex problems in designing intelligent systems with the ability to exploit the tolerance for imprecision, uncertainty and partial truth, to achieve tractability, robustness and low solution cost. So here explain all the terminologies in brief.

II. COMPUTATIONAL INTELLIGENCE

Computational intelligence is the study of the design of intelligent agents. An agent is something that acts in an environment—it does something. Agents include worms, dogs, thermostats, airplanes, humans, organizations, and society. An intelligent agent is a system that acts intelligently: What it does is appropriate for its circumstances and its goal, it is flexible to changing environments and changing goals, it learns from experience, and it makes appropriate choices given perceptual limitations and finite computation. The central scientific goal of computational intelligence is to understand the principles that make intelligent behavior possible, in natural or artificial systems. The main hypothesis is that reasoning is computation. The central engineering goal is to specify methods for the design of useful, intelligent artifacts. and artificial (or synthetic) systems, we prefer the name "computational intelligence."

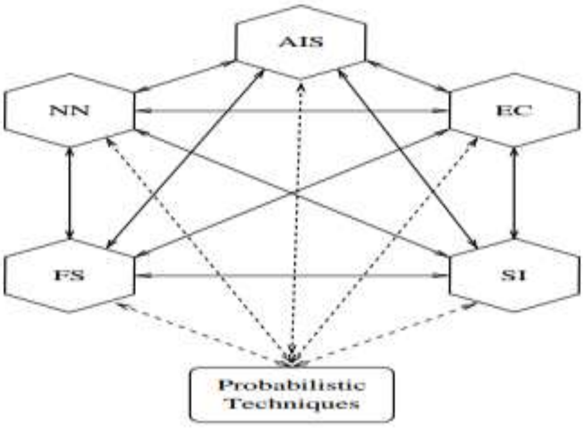

Figure 1 Computational Intelligence Paradigms

This paper considers five main paradigms of Computation Intelligence (CI), namely artificial neural networks (NN), evolutionary computation (EC), swarm intelligence (SI), artificial immune systems (AIS), and fuzzy systems (FS). Figure 1 gives a summary of the aim of the book. In addition to CI paradigms, probabilistic methods are frequently used together with CI techniques, which is also shown in the figure. Soft computing is a different grouping of paradigms, which usually refers to the collective set of CI paradigms and probabilistic methods. The arrows indicate that techniques from different paradigms can be combined to form hybrid systems. Each of the CI paradigms has its origins in biological systems. NNs model biological neural systems, EC models natural evolution (including genetic and behavioral evolution), SI models the social behavior of organisms living in swarms or colonies, AIS models the human immune system, and FS originated from studies of how organisms interact with their environment.

A. Artificial Neural Networks:

The brain is a complex, nonlinear and parallel computer. It has the ability to perform tasks such as pattern recognition, perception and motor control much faster than any computer – even though events occur in the nanosecond range for silicon gates, and milliseconds for neural systems. In addition to these characteristics, others such as the ability to learn, memorize and still generalize, prompted research in algorithmic modeling of biological neural systems – referred to as artificial neural networks (NN). It is estimated that there is in the order of 10-500 billion neurons in the human cortex, with 60 trillion synapses. The neurons are arranged in approximately 1000 main modules, each having about 500 neural networks. Will it then be possible to truly model the human brain? Not now. Current successes in neural modeling are for small artificial NNs aimed at solving a specific task. Problems with a single objective can be solved quite easily with moderate-sized NNs as constrained by the capabilities of modern computing power and storage space. The brain has, however, the ability to solve several problems simultaneously using distributed parts of the brain. We still have a long way to go ... The basic building blocks of biological neural systems are nerve cells, referred to as neurons. As illustrated in Figure 1.2, a neuron consists of a cell body, dendrites and an axon. Neurons are massively interconnected, where an interconnection is between the axon of one neuron and a dendrite of another neuron. This connection is referred to as a synapse. Signals propagate from the dendrites, through the cell body to the axon; from where the signals are propagated to all connected dendrites. A signal is transmitted to the axon of a neuron only when the cell "fires". A neuron can either inhibit or excite a signal.

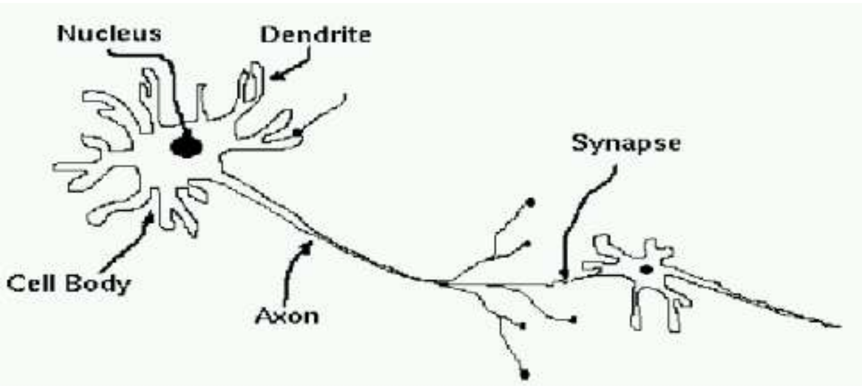

Figure 2. A Biological Neuron

An artificial neuron (AN) is a model of a biological neuron (BN). Each AN receives signals from the environment, or other ANs, gathers these signals, and when fired, transmits a signal to all connected ANs. Figure 1.3 is a representation of an artificial neuron. Input signals are inhibited or excited through negative and positive numerical weights associated with each connection to the AN. The firing of an AN and the strength of the exiting signal are controlled via a function, referred to as the activation function. The AN collects all incoming signals, and computes a net input signal as a function of the respective weights. The net input signal serves as input to the activation function which calculates the output signal of the AN.

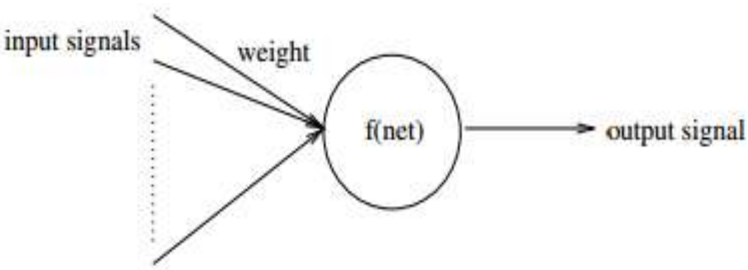

Figure 3. An Artificial Neuron

B. Evolutionary Computation:

Evolutionary computation (EC) has as its objective to mimic processes from natural evolution, where the main concept is survival of the fittest: the weak must die. In natural evolution, survival is achieved through reproduction. Offspring, reproduced from two parents (sometimes more than two), contain genetic material of both (or all) parents – hopefully the best characteristics of each parent. Those individuals that inherit bad characteristics are weak and lose the battle to survive. This is nicely illustrated in some bird species where one hatchling manages to get more food, gets stronger, and at the end kicks out all its siblings from the nest to die. Evolutionary algorithms use a population of individuals, where an individual is referred to as a chromosome. A chromosome defines the characteristics of individuals in the population. Each characteristic is referred to as a gene. The value of a gene is referred to as an allele. For each generation, individuals compete to reproduce offspring. Those individuals with the best survival capabilities have the best chance to reproduce. Offspring are generated by combining parts of the parents, a process referred to as crossover. Each individual in the population can also undergo mutation which alters some of the allele of the chromosome. The survival strength of an individual is measured using a fitness function which reflects the objectives and constraints of the problem to be solved. After each generation, individuals may undergo culling, or individuals may survive to the next generation (referred to as elitism). Additionally, behavioral characteristics (as encapsulated in phenotypes) can be used to influence the evolutionary process in two ways: phenotypes may influence genetic changes, and/or behavioral characteristics evolve separately. Different classes of evolutionary algorithms (EA) have been developed like Genetic algorithms, Genetic programming, Evolutionary programming, Evolution strategies, Differential evolution, Cultural evolution, Convolution.

C. Swarm Intelligence:

Swarm intelligence (SI) originated from the study of colonies, or swarms of social organisms. Studies of the social behavior of organisms (individuals) in swarms prompted the design of very efficient optimization and clustering algorithms. For example, simulation studies of the graceful, but unpredictable, choreography of bird flocks led to the design of the particle swarm optimization algorithm, and studies of the foraging behavior of ants resulted in ant colony optimization algorithms. Particle swarm optimization (PSO) is a stochastic optimization approach, modeled on the social behavior of bird flocks. PSO is a population-based search procedure where the individuals, referred to as particles, are grouped into a swarm. Each particle in the swarm represents a candidate solution to the optimization problem. In a PSO system, each particle is "flown" through the multidimensional search space, adjusting its position in search space according to its own experience and that of neighboring particles. A particle therefore makes use of the best position encountered by itself and the best position of its neighbors to position itself toward an optimum solution. The effect is that particles "fly" toward an optimum, while still searching a wide area around the current best solution. The performance of each particle (i.e. the "closeness" of a particle to the global minimum) is measured according to a predefined fitness function which is related to the problem being solved. Applications of PSO include function approximation, clustering, optimization of mechanical structures, and solving systems of equations.

D. Artificial Immune Systems:

The natural immune system (NIS) has an amazing pattern matching ability, used to distinguish between foreign cells entering the body (referred to as non-self, or antigen) and the cells belonging to the body (referred to as self). As the NIS encounters antigen. After the text edit has been completed, the paper is ready for the template. Duplicate the template file by using the Save As command, and use the naming convention prescribed by your conference for the name of your paper. In this newly created file, highlight all of the contents and import your prepared text file. You are now ready to style your paper; use the scroll down window on the left of the MS Word Formatting toolbar. the adaptive nature of the NIS is exhibited, with the NIS memorizing the structure of these antigen for faster future response the antigen. In NIS research, four models of the NIS can be found:

- **The classical view** of the immune system is that the immune system distinguishes between self and non-self, using lymphocytes produced in the lymphoid organs. These lymphocytes "learn" to bind to antigen.
- **Clonal selection theory**, where an active B-Cell produces antibodies through a cloning process. The produced clones are also mutated.
- **Danger theory**, where the immune system has the ability to distinguish between dangerous and non-dangerous antigen.
- **Network theory**, where it is assumed that B-Cells form a network. When a B-Cell responds to an antigen, that B-Cell becomes activated and stimulates all other B-Cells to which it is connected in the network. An artificial immune system (AIS) models some of the aspects of a NIS, and is mainly applied to solve pattern recognition problems, to perform classification tasks, and to cluster data. One of the main application areas of AISs is in anomaly detection, such as fraud detection, and computer virus detection.

E. Fuzzy Systems:

Traditional set theory requires elements to be either part of a set or not. Similarly, binary-valued logic requires the values of parameters to be either 0 or 1, with similar constraints on the outcome of an inferencing process. Human reasoning is, however, almost always not this exact. Our observations and reasoning usually include a measure of uncertainty. For example, humans are capable of understanding the sentence: “Some Computer Science students can program in most languages”. But how can a computer represent and reason with this fact? Fuzzy sets and fuzzy logic allow what is referred to as approximate reasoning. With fuzzy sets, an element belongs to a set to a certain degree of certainty. Fuzzy logic allows reasoning with these uncertain facts to infer new facts, with a degree of certainty associated with each fact. In a sense, fuzzy sets and logic allow the modeling of common sense. The uncertainty in fuzzy systems is referred to as no statistical uncertainty, and should not be confused with statistical uncertainty. Statistical uncertainty is based on the laws of probability, whereas no statistical uncertainty is based on vagueness, imprecision and/or ambiguity. Statistical uncertainty is resolved through observations. For example, when a coin is tossed we are certain what the outcome is, while before tossing the coin, we know that the probability of each outcome is 50%. No statistical uncertainty, or fuzziness, is an inherent property of a system and cannot be altered or resolved by observations. Fuzzy systems have been applied successfully to control systems, gear transmission and braking systems in vehicles, controlling lifts, home appliances, controlling traffic signals, and many others.

III. GRANULAR COMPUTING

Granular computing (GRC) is an emerging computing paradigm of information processing. It concerns the processing of complex information entities called information granules, which arise in the process of data abstraction and derivation of knowledge from information or data. Generally speaking, information granules are collections of entities that usually originate at the numeric level and are arranged together due to their similarity, functional or physical adjacency, in distinguish ability, coherency, or the like. At present, granular computing is more a theoretical perspective than a coherent set of methods or principles. As a theoretical perspective, it encourages an approach to data that recognizes and exploits the knowledge present in data at various levels of resolution or scales. In this sense, it encompasses all methods which provide flexibility and adaptability in the resolution at which knowledge or information is extracted and represented.

Figure 4. Small scale representation of data.

A. Why granular computing?

There are many reasons for the study of granular computing. The previous discussion provides some motivations. They stem mainly from the use of levels of granularity. The following list summarizes and reiterates some of the points:

1. **Truthful representation of the real world.** Many natur al, social, and artificial systems are organized into levels. Granular computing provides true and natural representations of such systems. Through the multiple level representation, one can obtain a full understanding of a system.
2. **Consistent with human thinking and problem solving**. Human problem solving is based crucially on levels of granularity and change between granularities. Granular computing therefore extracts the common elements from human problem solving. The implementation of the principles of granular computing would lead to more effective information processing systems.
3. **Simplification of problems**. A multiple level representation shows the orderness, the control, and the organization of a complex system or a complex problem. Different levels focus on different granularities

characterized by different grain sizes. By omitting unnecessary, irrelevant details and focusing on the right level of abstraction, we are able to simplify a complex system, or a complex problem.

4. **Economic and low cost solutions.** By considering the same problem at different levels of granularity, we ignore some details. This in turn may lead to approximate and inaccurate solutions. A benefit is that such solutions can normally be obtained economically at a fraction of the cost.

B. Granular Computing triangle:

There are basically five types of granulation: Value Granulation, Variable Granulation, System Granulation. Concept Granulation. Granular computing is usually studies from three perspectives that are : Philosophical perspective, Methodological perspective and Computational perspective. These are included as the main components of granular triangle.

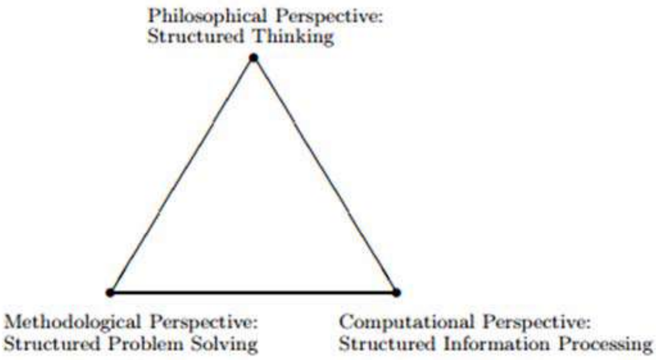

Figure 5 Granular Computing triangle.

There are also different interpretations of granular computing like framework of theories, methodologies, techniques, and tools that make use of information granules in the process of problem solving. We elaborate on the rationale behind granular computing. Next, a number of formal frameworks of information granulation are discussed including several alternatives such as fuzzy sets, interval analysis, rough sets, and probability. The notion of granularity itself is defined and quantified. A design agenda of granular computing is formulated and the key design problems are raised. A number of granular architectures are also discussed with an objective of delineating the fundamental algorithmic, and conceptual challenges. It is shown that the use of information granules of different size (granularity) lends itself to general pyramid architectures of information processing. The role of encoding and decoding mechanisms visible in this setting is also discussed in detail, along with some particular solutions. We raise an issue of interoperability of granular environments. One of the main application of Granular computing will be in making intelligent computational systems and data mining processes.

IV. SOFT COMPUTING

Soft computing is based on natural as well as artificial ideas. It is referred as a computational intelligence. It differs from conventional computing that is hard computing. It is tolerance of imprecision, uncertainty, partial truth to achieve tractability, approximation, robustness, low solution cost, and better rapport with reality. In fact the role model for soft computing is human mind. It refers to a collection of computational techniques in computer science, artificial intelligence, machine learning applied in engineering areas such as Aircraft, spacecraft, cooling and heating, communication network, mobile robot, inverters and converters, electric power system, power electronics and motion control etc. Traditionally soft computing has been comprised by four technical disciplines. The first two, probabilistic reasoning (PR), and fuzzy logic (FL) reasoning systems, are based on knowledge-driven reasoning.

The other two technical disciplines, Neuro Computing (NC) and Evolutionary Computing (EC), are data – driven search and optimization approaches. Soft computing is not a mélange. Rather, it is a partnership is which each of the constituent contributes a distinct methodology for addressing problem in its domain. In this perspective, the principal constituent methodologies in soft computing are complementary rather than competitive. In fact, soft computing’s main characteristic is its intrinsic capability to create hybrid systems that are based on the integration of constituent technologies. This integration provides complementary reasoning and searching methods that allow us to combine domain knowledge and empirical data to develop flexible computing tools and solve complex problems. Hybrid computing is the combination of hard computing and soft computing which having their inherent advantages and disadvantages.

To get the advantages of both these techniques their individuals limitations are reduced for solving a problem more efficiently by Hybrid computing. Hybrid soft computing models have been applied to a large number of classification, prediction, and control problems. Soft computing is yet another field in intelligence. Where is the main supporting system for computational intelligence. Soft computing usually focuses on solutions of an intelligent system which are unpredictable i.e. between 0 and 1. Soft computing was developed in the early 1990's and became a part of the studies in the intelligent agents. Soft computing has its counter-part which is hard computing which is rather a support system for artificial intelligence. Unlike hard computing, soft computing is tolerant to imprecision, uncertain data, partial truth and approximations, whereas hard computing works on concrete data like true or false. The main motive of the soft computing is to exploit the tolerance of imperfect data to achieve tractability, robustness and low solution cost. In the contemporary world, soft computing is often used to make prediction technologies like bio-medicine prediction, weather prediction and making of intelligent personal assistants. Again the main components of soft computing are fuzzy logic, neural networks, machine learning and probabilistic methods. Strikingly interesting products like washing machines, air conditioners etc. use the "neurofuzzy" systems which are the core branches of soft computing. The employment of soft computing technologies leads to systems which have high Machine intelligence quotient.

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