Preface

Multimedia uses multiple forms of information content and processing mainly text, audio, graphics, animation, and video for communication to cater the various user demands. Today, multimedia presentation, etc. are used in movies, education, entertainment, marketing, advertising, information services, teleconferencing, publishing, interactive television, product demonstration, and alike. Because of the rapid transfer of information and a growing need to present this information in a powerful way, only individuals who have appropriate skills and knowledge to communicate effectively will succeed in the multimedia industry.

In the last few years, multimedia processing has emerged as an important technology to generate contents based on images, audio, graphics, animation, full-motion video, and text, and it has opened a wide range of applications by combining these different of information sources thus giving insights in the interpretation of the multimedia content. Furthermore, recent new developments such as the high-definition multimedia content and interactive television can lead to the generation of a huge volume of data and imply serious computing problems connected with the creation, processing, and management of multimedia content. Multimedia processing is a challenging domain for several reasons as: it requires both high-computational processing requirements and memory bandwidth; it is a multi-rate computing problem; and it requires low-cost implementations for high-volume markets.

Computational intelligence is one of the most exciting and rapidly expanding fields which attract a large number of scholars, researchers, engineers and practitioners working in such areas as rough sets, neural networks, fuzzy logic, evolutionary computing, artificial immune systems, and swarm intelligence. Computational intelligence has been a tremendously active area of research for the past decade or so. There are many successful applications of computational intelligence in many subfields of multimedia, including image processing or retrieval, audio processing, and text processing. However, there are still numerous open problems in multimedia processing exemplified by multimedia communication, multimedia computing and computer animation

that need advanced and efficient computational methodologies desperately to deal with the huge volumes of data generated by these problems.

This volume provides an up-to-date and state-of-the-art coverage of diverse aspects related to computational intelligence in multimedia processing. It addresses the use of different computational intelligence-based approaches to various problems in multimedia computing, networking and communications such as video processing, virtual reality, movies, audio processing, information graphics in multimodal documents, multimedia tasks scheduling, modeling interactive nonlinear stories, video authentication, text localization in images, organizing multimedia information, and visual sensor networks. This volume comprises of 19 chapters including an overview chapter providing an up-to-date and state-of-the review of the current literature on computational intelligence-based approaches to various problems in multimedia computing and communication, and some important research challenges.

The book is divided into five parts devoted to: foundation of computational intelligence in multimedia processing, computational intelligence in 3D multimedia virtual environment and video games, computational intelligence in image/audio processing, computational intelligence in multimedia networks task scheduling; and computational intelligence in video processing.

The part on *Foundation of computational intelligence in multimedia processing* contains two introductory chapters. It presents a broad overview of computational intelligence (CI) techniques including Neural Network (NN), Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Fuzzy Set (FS), Reinforcement Learning (RL) and Rough Sets (RS). In addition, a very brief introduction to near sets and near images which offer a generalization of traditional rough set theory and a new approach to classifying perceptual objects by means of features in solving multimedia problems is presented. A review of the current literature on CI-based approaches to various problems in multimedia computing, networking and communications is presented. Challenges to be addressed and future directions of research are also presented.

Chapter 1, by *Aboul-Ella Hassanien, Ajith Abraham, Janusz Kacprzyk*, and *James F. Peters,* presents a review of the current literature on computational intelligence-based approaches to various problems in the multimedia computing such as speech, audio and image processing, video watermarking, content-based multimedia indexing, and retrieval. The chapter also discusses some representative methods to provide inspiring examples to illustrate how CI could be applied to resolve multimedia computing problems and how multimedia could be analyzed, processed, and characterized by computational intelligence.

Chapter 2, by *Parthasarathy Guturu*, presents a review of the current literature on computational intelligence-based approaches to various problems in multimedia networking and communications such as call admission control, management of resources and traffic, routing, multicasting, media composi-

tion, encoding, media streaming and synchronization, and on-demand servers and services.

The part on *Computational intelligence in 3D multimedia virtual environment and video games* contains four chapters. It discusses the application of computational intelligence techniques in the area of virtual environment (in which humans can interact with a virtual 3D scene and navigate through a virtual environment) and music information retrieval approaches. Dynamic models are also employed to obtain a more formal design process for (story-driven) games and on improving the current approaches to interactive storytelling.

In Chap. 3, *Ronald Genswaider, Helmut Berger, Michael Dittenbach, Andreas Pesenhofer, Dieter Merkl, Andreas Rauber,* and *Thomas Lidy* introduce the MediaSquare, a synthetic 3D multimedia environment that allows multiple users to collectively explore multimedia data and interact with each other. The data is organized within the 3D virtual world either based on content similarity, or by mapping a given structure (e.g. a branch of a file system hierarchy) into a room structure. With this system it is possible to take advantage of spatial metaphors such as relations between items in space, proximity and action, common reference and orientation, as well as reciprocity.

In Chap. 4, *Tauseef Gulrez, Manolya Kavakli,* and *Alessandro Tognetti* developed a testbed for robot-mediated neurorehabilitation therapy that combines the use of robotics, computationally intelligent virtual reality, and haptic interfaces. They employed the theories of neuroscience and rehabilitation to develop methods for the treatment of neurological injuries such as stroke, spinal cord injury, and traumatic brain injury. As a sensor input they have used two state-of-the-art technologies, depicting the two different approaches to solve the mobility loss problem. In their experiment, a 52 piezo-resistive sensor laden shirt was used as an input device to capture the residual signals arising from the patient's body.

In Chap. 5, *Fabio Zambetta* builds the case for a story-driven approach to the design of a computer role-playing game using a mathematical model of political balance and conflict and scripting based on fuzzy logic. The model introduced differs from a standard HCP (hybrid control process) by the use of fuzzy logic (or fuzzy-state machines) to handle events, while an ordinary differential equation is needed to generate continuous level of conflict over time. By using this approach, not only can game designers express game play properties formally using a quasi-natural language, but they can also propose a diverse role-playing experience to their players. The interactive game stories designed with this methodology can change under the pressure of a variable political balance, and propose a different and innovative game play style.

Time flow is the distinctive structure of various kinds of data, such as multimedia movie, electrocardiogram, and stock price quote. To make good use of these data, locating desired instant or interval along the time is indispensable. In addition to domain specific methods like automatic TV program segmentation, there should be a common means to search these data according to

the changes along the time flow. Chapter 6, by *Ken Nakayama et al.* presents *I*-string and *I*-regular expression framework with some examples and a matching algorithm. *I*-string is a symbolic string-like annotation model for continuous media which has a virtual continuous branchless time flow. *I*-regular expression is a pattern language over *I*-string, which is an extension of conventional regular expression for text search. Although continuous media are often treated as a sequence of time-sliced data in practice, the framework adopts continuous time flow. This abstraction allows the annotation and search query to be independent from low-level implementation such as frame rate.

Computational intelligence in image/audio processing is the third part of the book. It contains six chapters discussing the application of computational intelligence techniques in image and audio processing.

In Chap. 7, *Barca J.C., Rumantir G.,* and *Li R.*, present a set of illuminated contour-based markers for optical motion capture that has been presented along with a modified K-means algorithm that can be used for removing inter-frame noise. The new markers appear to have features that solve and/or reduce several of the drawbacks associated with other marker systems currently available for optical motion capture. The new markers provide solutions to central problems with the current standard spherical flashing LED-based markers. The modified K-means algorithm that can be used for removing noise in optical motion capture data is guided by constraints on the compactness and number of data points per cluster. Experiments on the presented algorithm and findings in literature indicate that this noise-removing algorithm outperforms standard filtering algorithms such as the mean and median because it is capable of completely removing noise with both the spike and Gaussian characteristics.

In Chap. 8, *Sandra Carberry* and *Stephanie Elzer* present a corpus study that shows the importance of taking information graphics into account when processing a multimodal document. It then presents a Bayesian network approach to identifying the message conveyed by one kind of information graphic, simple bar charts, along with an evaluation of the graph understanding system.

In Chap. 9, *Klaas Bosteels* and *Etienne E. Kerre* present a recently introduced triparametric family of fuzzy similarity measures, together with several constraints on its parameters that warrant certain potentially desirable or useful properties. In particular, they present constraints for several forms of restrictability, which allow reducing the computation time in practical applications. They use some members of this family to construct various audio similarity measures based on spectrum histograms and fluctuation patterns.

Chapter 10, by *Przemysław Górecki*, *Laura Caponetti*, and *Ciro Castiello*, deals with the particular problem of text localization, which aims at determining the exact location where the text is situated inside a document image. The strict connection between text localization and image segmentation is highlighted in the chapter and a review of methods for image segmentation is proposed. Particularly, the benefits of this chapter and the employment of fuzzy and neuro-fuzzy techniques in this field are assessed, thus indicating

a way to combine computational intelligence methods and document image analysis. Three peculiar methods based on image segmentation are presented to show different applications of fuzzy and neuro-fuzzy techniques in the context of text localization.

In Chap. 11, *Kui Wu* and *Kim-Hui Yap*, present a soft-labeling framework that addresses the small sample problem in interactive CBIR systems. The technique incorporates soft-labeled images into the fuzzy support vector machine (FSVM) for effective learning along with labeled images for effective retrieval. By exploiting the characteristics of the labeled images, soft-labeled images are selected through an unsupervised clustering algorithm. Further, the relevance of the soft-labeled images is estimated using the fuzzy membership function. The FSVM-based active learning is then performed based on the hybrid of soft-labeled and explicitly labeled images. Experimental results based on a database of 10,000 images demonstrate the effectiveness of the proposed method.

Temporal textures are textures with motion like real world image sequences of sea-waves, smoke, etc. that possess some stationary properties over space and time. The motion assembly by a flock of flying birds, water streams, fluttering leaves, and waving flags also serve to illustrate such a motion. The characterization of temporal textures is of a vital importance to computer vision, electronic entertainment, and content-based video coding research with a number of potential applications in areas including recognition (automated surveillance and industrial monitoring), synthesis (animation and computer games), and segmentation (robot navigation and MPEG-4). Chapter 12, by *Ashfaqur Rahman* and *Manzur Murshed*, provides a comprehensive literature survey of the existing temporal texture characterization techniques.

The fourth part, Computational intelligence in multimedia networks and task scheduling contains four chapters that describe several approaches to develop video analysis and segmentation systems based on visual sensor networks using computational intelligence as well as a discussion about detecting hotspots in the cockpits in view of the Swissair 111 and ValuJet 592 flight disasters, and answer the question that how distributed sensor networks could help in near real-time event detection, disambiguating faults and events by using artificial intelligence techniques. In addition, it contains a chapter reviewing the current literature on computational intelligence-based approaches to various problems in multimedia networking and communications.

In Chap. 13, *Mitsuo Gen* and *Myungryun Yoo* discuss a task scheduling problem by introducing many scheduling algorithms for soft real-time tasks using a genetic algorithm (GA). They propose reasonable solutions for NP-hard scheduling problem with much less difficulties than those solved by traditional mathematical methods. In addition, a continuous task scheduling, real-time task scheduling on homogeneous system and real-time task scheduling on heterogeneous system are discussed and included in this chapter.

Chapter 14, by *Miguel A. Patricio, F. Castanedo, A. Berlanga, O. Pérez, J. Garćia*, and *José M. Molina,* describes several approaches to develop video

analysis and segmentation systems based on visual sensor networks using computational intelligence. They discuss how computational intelligence paradigms can help obtain competitive solutions. The knowledge about the domain is used in the form of fuzzy rules for data association and heuristic evaluation functions to optimize the design and guide the search of appropriate decisions.

In Chap. 15, *Sławomir T. Wierzchoń, Krzysztof Ciesielski,* and *Mieczysław A. Kłopotek*, focus on some problems concerning application of an immune-based algorithm to extraction and visualization of cluster structure. The chapter presents a novel approach, based on artificial immune systems, within a broad stream of map type clustering methods. Such approach leads to many interesting research issues, such as context-dependent dictionary reduction and keywords identification, topic-sensitive document summarization, subjective model visualization based on particular user's information requirements, dynamic adaptation of the document representation and local similarity measure computation.

In Chap. 16, *S. Srivathsan, N. Balakrishnan,* and *S.S. Iyengar* discuss some safety issues in commercial planes particularly focusing on hazards in the cockpit area. The chapter discusses a few methodologies to detect critical features and provides unambiguous information about the possible sources of hazards to the end user in near real time. They explore the application of Bayesian probability, the Iyengar–Krishnamachari method, probabilistic reasoning, reasoning under uncertainty, and the Dempster–Shafer theory, and analyze how these theories could help in the data analysis gathered from wireless sensor networks deployed in the cockpit area.

The final part of the book deals with the use of *computational intelligence in video processing.* It contains three chapters which discuss the use of computational intelligence techniques in video processing.

In Chap. 17, *Nicholas Vretos, Vassilios Solachidis,* and *Ioannis Pitas* provide a uniform framework by which media analysis can be rendered more useful for retrieval applications as well as for human-computer interaction-based application. All the algorithms presented in this chapter are focused on humans and thus provides interesting features for an anthropocentric analysis of a movie.

In Chap. 18, *Thomas Bärecke*, *Ewa Kijak, Marcin Detyniecki,* and *Andreas Nürnberger* present an innovative way of automatically organizing multimedia information to facilitate content-based browsing. It is based on self-organizing maps. The visualization capabilities of the self-organizing map provide an intuitive way of representing the distribution of data as well as the object similarities. The main idea is to visualize similar documents spatially close to each other, while the distance between different documents is larger. They introduce a novel time bar visualization that re-projects the temporal information.

In Chap. 19, *Mayank Vatsa, Richa Singh, Sanjay K. Singh,* and *Saurabh Upadhyay,* present an efficient intelligent video authentication algorithm using support vector machine. The proposed algorithm can detect multiple video tampering attacks. It computes the local relative correlation information and

classifies the video that is nontampered. The proposed algorithm computes the relative correlation information between all the adjacent frames of a video and projects them into a nonlinear SVM hyperplane to determine if the video is tampered or not. The algorithm is validated on an extensive video database containing 795 tampered and nontampered videos. The results show that the proposed algorithm yields a classification accuracy of 99.2%.

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Computational Intelligence in Multimedia Networking and Communications: Trends and Future Directions

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This paper presents a review of the current literature on computational intelligence based approaches to various problems in multimedia networking and communications such as call admission control, management of resources and traffic, routing, multicasting, media composition, encoding, media streaming and synchronization, and on-demand servers and services. Challenges to be addressed and future directions of research are also presented.

1 Introduction

We currently live in an age of information revolution. With high impact applications launched every day in various fields such as e-commerce, entertainment, education, medicine, defense, and homeland security, there has been an explosive growth in the demand for exchange of various forms of information, text, graphics, audio, video, etc. collectively termed as multimedia. Colossal amounts of multimedia data that need to be transmitted over the Internet, in turn, necessitate smart multimedia communication methods with capabilities to manage resources effectively, reason under uncertainty, and handle imprecise or incomplete information. To this end, many multimedia researchers in recent times have developed computational intelligence (CI) based methods for various aspects of multimedia communications. The objective of this book chapter is to present to the multimedia research community the state of the art in these CI applications to multimedia communications and networking, and motivate research in new trend-setting directions. Hence, we review in the following sections some representative CI methods for quality of service (QoS) provisioning by call/connection admission control, adaptive allocation of resources and traffic management. Some important contributions to multicast routing, multimedia composition, streaming and media synchronization, and multimedia services/servers are also surveyed. Most of the methods

available in the current literature are either fuzzy or neural network based though some papers adopted a hybrid approach of using neuro-fuzzy controllers. A few papers present genetic/evolutionary methods for problems in multimedia communications. From these applications, it appears that the various computational intelligence frameworks are not competitive, but rather complementary. For the sake of completeness, we present a brief review of the computational intelligence paradigm in the following subsection.

1.1 Computational Intelligence Paradigm

According to Wikipedia, the free online encyclopedia, computational intelligence (CI) is a branch of artificial intelligence (AI) that combines elements of learning, adaptation, evolution and fuzzy logic (as well as rough sets) to create programs equipped with intelligence to solve problems effectively. It uses meta-heuristic algorithms and strategies such as statistical learning machines, fuzzy systems, neural networks, evolutionary computation, swarm intelligence, artificial immune systems, etc. In contrast, the traditional AI (or, GOFAI, i.e., good old-fashioned artificial intelligence, as per the term coined by John Haugeland, professor of philosophy at the University of Chicago), relies on symbolic approaches. In this subsection, we present an overview of only those CI techniques that have been used in the multimedia communication and network research documents cited in the present survey.

Neural Networks

An artificial neural network (ANN) or simply neural network (NN) is an interconnected set of simple nonlinear processing elements called neurons because of their role similar to neurons in a biological system. The neurons in an ANN take inputs from either external environment or other neurons in the system. The neuronal outputs may similarly be transmitted to either other neurons (through interconnection weights) or external environment. The neurons that take inputs from and send outputs to exclusively other neurons are called hidden neurons. These hidden neurons have been found to be pivotal to learning of complex input–output mappings. The methods for adaptation of inter-neuron weights based on the observed outputs to obtain desired outputs are called NN training or learning methods. The NN interconnection patterns are called topologies. The most popular NN topology and the associated learning algorithm are feed-forward neural network (FFNN) and back-propagation learning (BPL) algorithm, respectively. FFNN is also known as multi-layer perceptron (MLP). In an FFNN, neurons are arranged into multiple layers consisting of an input, an output, and one or more hidden layers with unidirectional inter-layer neuronal connections (weights) from the input through to the output layer as shown in Fig. 1. Determination of inter-layer connection topologies, and the number of hidden layers as well as the number of neurons in each of them, based on the problem being solved, are open research issues.
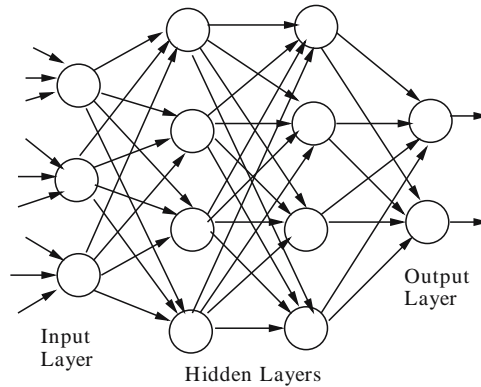
Fig. 1. A typical four layer feed-forward neural network

Still, simple three-layer FFNNs with total inter-connectivity between neurons in consecutive layers as shown in the figure have been successfully applied to multimedia and other applications where system adaptability and capability to learn complex functional dependencies of outputs on inputs are of paramount importance. The standard BPL algorithm used for training the FFNN interconnection weights is a supervised learning algorithm, i.e., one with a training set of input–output pairs). In this algorithm, the errors are first computed at the output layer as the differences between the desired and observed outputs for training sample inputs, and then the inter-neuronal connection weights from the neurons in the layer preceding the output layer to those in the output layer are updated (using mathematical formulae) to produce the desired outputs. The errors in the outputs of the previous stage neurons are also similarly computed, and the process of computing the weights and the neuron output is repeated for different layers in the FFNN proceeding in the backward direction till the input layer is reached. A detailed discussion of the FFNNs and the BPL may be found in [1].

A recurrent neural network is a generalized neural network in which bidirectional asymmetric interneuronal connections are possible; it does not need to have a layered organization of neurons. A recurrent NN training algorithm, which is similar to the BPL (because of almost the same mathematical formulae for updating interneuronal weights) and hence known as the recurrent back-propagation (RBP) algorithm, has been proposed independently by Almeida [2], and Pineda [3]. A special form of recurrent NN is the Hopfield neural net (HNN) [4], which uses binary threshold gates as processing elements (neurons), a totally connected network topology, and symmetric interneuronal connection weights. An HNN network may be configured to find the local optima (minima) of criterion functions in some problems if those functions can be cast in the form of the following energy function related the Ising model [5] in physics:

$$E = -\frac{1}{2} \sum_{i<j} \sum_{j} W_{ij} S_i S_j + \sum_i \theta_i S_i \qquad (1)$$

where W_{ij} is the interconnection-weight between the neurons i and j, S_i the binary (0 or 1) state (output) of the ith neuron, and θ_i is the threshold used to compute the output of the ith neuron from the sum of its input excitations.

Gelenbe [6] proposed a novel neural network model called the random neural network (RNN) and applied it various problems including those related to multimedia communications. The RNN is a set of neurons in which each neuron has a potential (an integer random variable). A neuron is said to be excited if its potential is strictly positive, and, in that state, it randomly sends signals (to other neurons or to the environment) according to a Poisson process with a specific rate. The potential of the neuron sending the signal is always decreased by 1 irrespective of whether the signal sent is positive or negative. The potential of a neuron receiving a signal from another neuron or the environment increased or decreased by 1 depending upon whether the signal received is positive or negative. In [6], Gelenbe establishes a connection between the RNN and queuing networks. The weights (actually, the probabilities for sending positive and negative signals from a neuron to another, and the probabilities for sending/receiving to/from an excitation from the environment) of an RNN can be trained using an algorithm resembling the back-propagation algorithm in the classical neural networks.

While the above discussed neural networks employ the supervised learning (learning with a teacher, i.e., a training set of pattern vectors with their classification labels) paradigm, self organized feature map (SOFM) proposed by Kohonen [7] is a neural network with capability to learn its own weights. A SOFM (sometimes called SOM) is modeled after the human brain in which different types of sensory information are processed by different parts. In a SOFM, each input is connected though a synaptic weight to all the output neurons arranged in a two or three dimensional grid. Thus every neuron in the system has an input weight vector with the same dimensionality as the input pattern vectors. At the beginning of the learning process, these weights are initialized to small random values. Then, as and when the pattern vectors are presented at the input of the network, and the neuronal weight vector which is the closest (according to the Euclidean distance measure) to the input pattern vector is determined. The corresponding neuron is called the BMU (best matching unit). The weight vectors of BMU and its neighbors on the grid are adjusted towards the input pattern. By repeated training with input patterns this way, the SOFM learns to produce neuronal activations in different locations of the network depending upon the input patterns. Once the network is completely trained this way, a new pattern may be input to the network and classified based on the location where the neuronal activity is produced. It may be noted here that input patterns used in the training phase are unlabeled samples, and hence the SOFM may be categorized an unsupervised learning method.

Reinforcement Learning

Mathematically, the reinforcement learning (RL) [8] system model is a triplet $M_{RIL} = \{\mathcal{S}, \mathcal{A}, \mathcal{R}\}$ where $\mathcal{S}$ is the set of states of a problem environment, $\mathcal{A}$ is the set actions that can be taken by an agent seeking to solve the problem, and $\mathcal{R}$ is the set of scalar rewards associated with an action and the current state of the system. In the RL paradigm, an agent perceives, at each time instant t, the current state $s_t (\in \mathcal{S})$ of the environment and the set of actions $\mathcal{A}(s_t) \subseteq \mathcal{A}$ that can be taken based on that state, and chooses an action $a \in \mathcal{A}(s_t)$. The chosen action results in a reward $r \in \mathcal{R}$, and drives the environment into a new state s_{t+1}. An RL formulation seeks to determine the optimal policy (or the series of actions the agent needs to take) to maximize the total reward. In this formulation, there is no concept of supervised learning of optimal system parameters by means of corrective actions based on the errors in the observed system outputs for a given training set of input–output pairs. Instead, the choice of actions is aided by the finite-state Markov decision process (MDP) [9] model of the environment. Even though it is not necessary to make use of ANNs for implementation of an RL formulation, it is usually the case to include them as a part of the solution.

Fuzzy Logic Based Intelligent Control

In any control system, the actions to control some aspect of system performance, e.g., congestion control, maximum end-to-end delay in the network) are based on the system inputs, e.g., message packet loss, link delay). However, for robust control, the system needs to be capable of managing the uncertainties in the system environment and imprecisions in the system input measurements. A mathematical formalism useful for the design of such robust systems was pioneered by Zadeh [10], and was first applied by Mamdani [11] to control system design. It is variously known as fuzzy set theory or fuzzy logic. The logic variables, e.g., congestion) in fuzzy set theory do not take crisp binary (false or true) values, but take continuous values (called membership values) in the range [0,1]. Another class of fuzzy logic variables that capture our vague, ambiguous, qualitative or subjective view of the world are termed as linguistic variables. They may be loosely defined as variables that take graded membership or simply linguistic values, e.g., high, medium, low, rough, smooth, etc.). Modern fuzzy control systems use a set of fuzzy linguistic rules of the form given below to derive inferences about the output variables from the input variables and use the output estimates so obtained for control:

If packet loss is *low*, and network delay is *high*, network congestion is medium.

Since such rules are gathered from experts in the field, such control systems come under the class of Fuzzy Expert Systems. Each rule (proposition) in
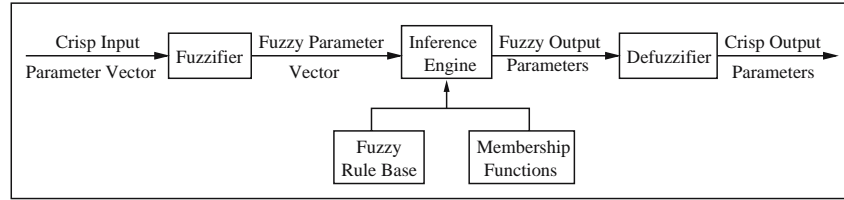
Fig. 2. Block diagram of a fuzzy logic system

the rule base of the fuzzy control system is associated with a membership value (degree of truth) in the range [0,1]. The membership values of various applicable propositions are aggregated by a properly designed inference engine in a fuzzy logic system and the system outputs are estimated. Figure 2 depicts the block diagram of a typical fuzzy logic based system for obtaining the control parameters with the problem state vector as its input.

The fuzzifier module in the system converts the crisp input values into linguistic values such as high and medium so that inference engine can generate the fuzzy values for the output parameters using rules such as the one indicated above from the rule base. In case of applicability of more than one rule, the membership values of different rules are aggregated to obtain a consistent estimate. The defuzzifier then converts the fuzzy values of the output variables into crisp values. In this article, a few neuro-fuzzy applications to multimedia communications are also presented. These methods typically use neural networks for learning both the rules and the membership functions associated with the rules.

Rough Sets

Rough set theory (RST) is another approximate reasoning formalism developed for handling imprecision. Here, the values of a set of attributes are represented by two sets: one for the lower and the other for the upper approximation the original crisp set. Even though the upper and lower sets in the original formalism of Pawlak [12] are crisp sets, they could as well be fuzzy sets. A rough set inference mechanism similar to fuzzy inferencing could be used for estimation of system parameters. The RST uses the an information system framework (ISF) $\mathcal{I}$, which may be defined as a tuple $(\mathcal{O}, \mathcal{A})$, where $\mathcal{O}$ is a non-empty set of objects, and $\mathcal{A}$ is a set of their attributes. In ISF, an information table maps the value tuples (of the attributes) onto the objects. Two objects are defined to be discernible if they can be distriguished based on their value tuples. This discernability relationship between objects induces an equivalent partition among the objects. In case each partition so obtained is a singleton, the every object of the system can be distinguished from the given set of attributes. Now, when we consider a subset of the attribute set $\mathcal{A}$, the target set $\mathcal{T}(\subseteq \mathcal{O})$ of objects cannot be expressible exactly because some subsets of objects in $\mathcal{T}$ could be indiscernable. Hence a rough set involving

an upper approximation set of objects *possibly* in the target and a lower approximation set of objects *positively* in the target may be used to represent the target. From the rough sets so constructed, it is possible to obtain reduct subsets of attributes, that is, the subsets of attributes, each of which induce the same equivalent partition on $\mathcal{O}$ as the original set $\mathcal{A}$. The reduct subset is not unique, because different subsets of $\mathcal{A}$ could induce the same equivalent partition. The intersection of such reduct subsets gives the core (or indispensable) set of attributes of the information system $\mathcal{I}$. Similarly, when the union of all reduct sets is removed from $\mathcal{A}$, we get the set of superfluous attributes. Thus the rough set is a useful tool for capturing the knowledge represented in the information system with lesser number of attributes.

Dubois [13] extended the formalism of RST by introducing rough fuzzy sets and fuzzy rough sets. Among the applications of RST, the RST based approaches proposed by Stefanowski [14] for induction of decision rules, and Ziarko's [15] rough set methodology for data mining are worth mentioning.

Evolutionary Computation

Evolutionary computation (EC) is the generic name for a number of allied biology-inspired technologies such as evolutionary programming (EP) [16], genetic algorithms (GAs) [17], evolution strategies (ES) [18, 19], and genetic programming (GP) [20]. The goal of an EC algorithm is to find a quasi-optimal solution to a problem by mimicking the genetic evolutionary processes. Particularly when the optimality measure on a large set of variables characterizing the problem solution turns out to be a non-convex multi-modal function, an exhaustive search for an optimal solution is ruled out because of exponential search complexity. In this situation, the EC approach is an effective strategy for intelligent exploration of the search space to find near-optimal solutions. In this approach, the search starts with an initial population of candidate solutions, each represented by a vector of randomly chosen values for the problem solution variables. Now, based on an analogy between the process for obtaining optimal solution and genetic evolution, the solution vector may be considered as an equivalent of a chromosome with individual components of the vector representing the genes. The optimality measures (or equivalently, the fitness functions) of the individual candidate solutions in any generation including the initial one may be computed using the functional form of the measure, and the solutions may be ordered based on their fitness values. The candidate solutions for the next generation (offsprings) may then be obtained by using a crossover operation on parent solutions usually chosen from the population of the current generation, using the so-called elitist strategy, that is, the strategy of choosing the participants of the cross-over randomly from a selected few members (with the highest fitness value) of the population of the current generation. The traditional crossover is based on the concept of exchange of the genetic material between parents (without many constraints), but one can also design a new crossover mechanism, based on a given optimization

problem being dealt with. Crossover points are also chosen randomly. Another very important genetic operator, next to the above discussed crossover, used in EAs is mutation. It simulates genetic mutation by replacing the value of a randomly chosen component of solution vector with a new value from the set of values admitted for the component. By producing successive generations of new populations by selective replacement of the members of an old generation by the fittest among the new members (offsprings) produced with the help of the two operators discussed above, genetic evolution may be continued for a number of generations to obtain solutions closer and closer to optimality. Problem representation, design of crossover and mutation operators, strategies for replacement of the members of the old population with new members, and optimal choice of EC parameters such as population size, number of generations for evolution, etc. are open research issues of this area.

2 Call/Connection Admission Control

Call admission control (CAC) is a mechanism to determine whether resources requested by an incoming multimedia call could be reserved without adversely affecting the QoS requirements of the on-going calls. In ATM multimedia networks, this is tantamount to connection admission control (with the same abbreviation: CAC), which is a decision-making process to accept or reject a request for a new virtual path (VP) or virtual channel (VC) based on the anticipated traffic characteristics of the connection, the requested QoS, and the current state of the network. Traditional CAC schemes make use of various criteria for call/connection admission such as equivalent capacity or bandwidth requirements of various links, maximum allowable cell loss probability, network traffic load, *etc.* To address some deficiencies of these methods such as failure to meet QoS requirements in heavy traffic conditions, computational intensiveness of the call parameter estimation methods, etc. a number of CI-based CAC methods have been proposed in the literature. In the sequel, we discuss a few representative methods.

One of the earliest CI-based approaches to multimedia CAC in ATM networks is due to Hiramatsu [21]. In this approach, he uses a three-layer feed-forward neural network (FFNN) with the standard back-propagation learning algorithm to obtain predicted service quality parameters and call acceptance/rejection decision values (such as predicted values for call arrival rate and cell loss rate, and the call rejection rate) with observed multiplexer status parameters such as cell arrival rate, cell loss rate (CLR), call generation rate, trunk utilization rate, number of connected calls, as the FFNN inputs. Simulation results indicate the adaptability of the proposed method in learning complex admission control decision policies. In [22], he addresses the problem of training neural networks with exponentially wide ranged QoS parameters, e.g., CLR ranging from 10^{-12} to 1) using two methods: (i) training with a relative target: here the neural network is assumed to memorize the

logarithm of the average of K-recent monitored QoS values, and the new target is an updated average derived from a weighted summation of a new sample and the memorized QoS, and (ii) virtual output buffer method wherein a neural network is trained to accurately estimate the QoS for the actual buffer by incremental extrapolations using the data from smaller capability virtual buffers (a set of counters simulating an imaginary cell buffering process).

Youssef, Habib, and Saadawi [23] propose a neurocomputing approach to CAC and bandwidth allocation in ATM networks. The algorithm proposed by them employs a hierarchical structure of a bank of small-sized parallel neural network (NN) units to calculate efficiently the bandwidth required to support multimedia traffic with multiple QOS requirements. Each NN unit is a FFNN trained using the standard back-propagation algorithm the complex nonlinear function relating different traffic patterns and QoS, with the corresponding received capacity. The NN controller calculates the gain obtained from multiplexing multiple streams of traffic supported on separate virtual paths, i.e., class multiplexing) also so as to enhance the statistical multiplexing gain. The authors use simulation results to prove that their NN approach is more accurate in bandwidth calculations and consequently CAC decision-making compared to two conventional approaches that use the stationary state approximation of the equivalent capacity method [24], and class related rule [25], respectively.

References [26] and [27] independently propose fuzzy approaches for estimation of the CLR, which is an important CAC parameter. In [26], Uehara and Hirota estimate possibility distribution of the CLR as a function of the number of calls in different transmission rate classes. Starting with an initial fuzzy rule base for CLR estimation, successive generations of fuzzy inference rules are generated by incremental updates based on the CLR data observed from time to time. A back-propagation algorithm (unrelated to the neural network algorithm with the same name) is used for tuning the rule base with new data. Using fuzzy α-cut theory [28], self-compensation of CLR estimation errors is achieved, and then, by applying the latest rule base, an upper bound on the CLR estimate is obtained and used for CAC decision making. Bensaou et al. [27] propose a robust fuzzy based algorithm to predict the CLR in ATM multiplexers, and use the CLR estimate so obtained for call admission control. Unlike many traditional approaches, their method does not presume any input traffic model or parameters, but employs the knowledge of a set of CLR values for small values of an independent variable, e.g., multiplexer buffer size or service capacity) of the CLR function, in conjunction with the knowledge of the asymptotic behavior of the function for larger values of the variable.

In [29], Ren and Ramamurthy propose a dynamic CAC (for ATM multimedia networks) that employs fuzzy logic to combine a CAC based on the UPC (user parameter control) model with that based on measured online traffic statistics for determining the dynamic equivalent bandwidth used in CAC decision making. Simulation results indicate that substantially improved system

utilization can be achieved with dynamic CAC compared to a model-based or a measurement-based CAC.

Liang, Karnik, and Mendel [30] propose an interesting connection admission control algorithm for ATM networks that uses type-2 fuzzy logic rule base incorporating the knowledge obtained from 30 network experts. In type-2 fuzzy logic, the membership value of each element in the fuzzy set is itself fuzzy. The type-2 fuzzy logic used in their system , in contrast to type-1 fuzzy logic, provides soft decision boundaries, and thereby permits tradeoff between CLR and bandwidth utilization.

Cheng, Chang, and their coworkers are one of the earliest to adopt a hybrid CI approach to call admission control. An IEEE journal article [31] and a US patent document [32] together present the details of their neural fuzzy CAC (NFCAC). The NFCAC takes in three linguistic inputs, available capacity, congestion indicator, and cell loss ratio, and outputs a decision signal to accept or reject a new call request. The fuzzy estimates of the available capacity and the congestion indicator are, in turn, done by a fuzzy bandwidth estimator and a fuzzy congestion controller proposed in their earlier work [33]. The NFCAC is a five layered feed-forward neural network with a two-phase hybrid learning algorithm. Construction of fuzzy rules and location of membership functions is done by a self-organized learning scheme in phase-I whereas optimal adjustment of membership functions for desired outputs is done by a supervised learning scheme in phase-II. The authors show by means of simulation results that their NFCAC, despite the simplicity of its design, can satisfy the QoS requirements, and still achieve higher system utilization and learning speed compared to a traditional effective-bandwidth-based CAC [34], and the fuzzy-logic-based [33] and neural-net-based [35] CACs proposed by them earlier.

In [36], Chatovich, Oktug, and Dundar propose a hierarchical neural-fuzzy connection admission controller for ATM multimedia networks. This CAC is based on Berenji and Khedkar's GARIC (Generalized Approximate Reasoning-based Intelligent Controller) architecture [37] that includes two co-operating neural networks, one called ASN (Action Selection Network) for implementing fuzzy inference rules initially acquired from an expert, and the other called AEN (Action Evaluation Network) for performance evaluation and fine tuning of the former by the reinforcement learning approach. The ASN is organized as a hierarchical structure that combines three sub-controllers, one for each one of the three system variables, CLR, queue size, and link utilization, and comes up with the final decision by weighted aggregation of the decisions of the three sub-controllers.

In [38], Shen et al. address the problem of bursty wireless multimedia traffic with unpredictable statistical fluctuations in wide-band CDMA (Code Division Multiple Access) cellular systems, and propose an intelligent CAC (ICAC) that makes call admission decisions based on QoS parameters such as handoff call drop probability, outage probabilities of various service types, existing-call interference estimates, the link gain, and the estimate of

equivalent interference of the call request. Estimation of the existing call interference in ICAC is done by a pipeline recurrent neural net (PRNN) which predicts the mean value of the system interference for the next period as a function of p: measured interference powers, and q: previously predicted interference powers, where p and q are the fuzzy estimator subsystem parameters. For equivalent interference estimation, ICAC uses a fuzzy estimator that takes in as input four parameters of the new call: peak and mean traffic rates, peak traffic duration, and the outage probability requirement. The fuzzy call admission processor of ICAC uses the two interference estimates provided by the fuzzy estimator and PRNN in conjunction with other QoS information to make a four-fold decision: {Strong Accept, Weak Accept, Weak Reject, Strong Reject}. Simulation results comparing ICAC with two traditional CAC methods, namely PSIR-CAC (predicted signal-to-interference ratio CAC) and MCAC (Multimedia CAC), indicate that ICAC achieves higher system capacity than PSIR-CAC and MCAC by more than 10% in traffic ranges where QoS requirements are guaranteed. The ICAC has been found to fulfill the multiple QoS requirements under all traffic load conditions whereas conventional CAC schemes fail under heavy traffic load conditions.

Ahn and Ramakrishna [39] propose an interesting Hopfield neural network (HNN) based CAC algorithm for QoS provisioning in wireless multimedia networks. The QoS provisioning problem is formulated as a multi-objective optimization problem that seeks to maximize the twin objectives of resource utilization and fair distribution of resources (among different connections) subject to the constraint that the total allocated bandwidth cannot exceed the available capacity. The authors show that the overall objective function can be cast into the form of HNN energy function given in the equation (1) so that an HNN with $n \times m$ neurons (for an n-connection m-QoS level problem) can be set up to minimize the energy function and produce stable and feasible QoS vector values.

In [40], Sinouci, Beylot and Pujolle formulate call admission control as a semi-Markov decision problem (SMDP), and develop a reinforcement learning (neuro-dynamic programming) based algorithm for construction of a dynamic call admission policy. The algorithm is implemented using both table lookup and feed-forward neural network approaches for determination of the Q-values (state-action tuples) of their system based on the number of current calls in two traffic classes, and the characteristics of the new call, e.g., handoff or new, class 1 or class 2 type). Call admission decision (accept or reject) is made using the action value obtained using this approach, and the system is trained using the reward associated with success of accepted calls. Their neural network based CAC is naturally more memory efficient compared to the table lookup implementation. The proposed method yields an optimal solution at much higher speed compared to traditional approaches, which are also difficult to optimize.

For the reverse link transmission in the wideband code division multiple access (WCDMA) cellular systems, Ye, Shen, and Mark propose a CAC

scheme using fuzzy logic [41]. In their scheme, a fuzzy call admission processor uses the estimates on the effective bandwidth and network resources along with the QoS parameters as inputs to output a call acceptance or rejection decision. Effective bandwidth, in turn, is estimated by a fuzzy estimator using call request parameters and pilot signal strength information as inputs. Pilot signal strength is also used by a fuzzy estimator to produce mobility estimate, which is used in conjunction with the effective bandwidth and bit energy to noise-plus-interference density ratio of the traffic class under consideration by a fuzzy network resource estimator to produce the network resource estimate required by the fuzzy call admission processor. The authors provide simulation results to compare their approach with two previously proposed traditional CAC schemes, received power-based call admission control (RPCAC) [42] and non-predictive call admission control (NPCAC) [43], and demonstrate its effectiveness in terms of new and handoff call blocking probabilities, outage probability, and resource utilization.

3 Adaptive Allocation and Management of Resources

Allocation of resources is intimately related to call admission control and QoS management. Hence, in case of multimedia applications requiring high throughput, it turns out to be a problem of paramount significance that needs to be handled intelligently. Considering the need for continual revision of bandwidth allocations to different calls in high traffic situations, Sherif *et al.* [44] propose a genetic algorithmic approach to adaptive allocation of resources and call admission control in wireless ATM networks. In their scheme, QoS requirements for each of the video, audio, and data sub-streams of a multimedia call can be specified from a 4-tuple {High, Medium, Low, Stream Dropped} with the possibility for a total of 64 (4^3) Q-values for the call as a whole. Assuming that the maximum to minimum Q-value range for each call is available from the user data profile, they formulate the problem of adaptive allocation (in contrast to the traditional static allocation) of bandwidth for existing calls as an optimization problem to minimize the spare capacity (after call allocation) in the cell without either overshooting the cell capacity or going below the minimum Q-value of any call in the cell. This, being a non-convex optimization problem, has been solved using the genetic approach. Simulation results indicate the adaptability of the algorithm to high traffic situations, graceful degradation of individual user QoS levels with load, and effective and fair utilization of available bandwidth with increased number of admitted calls.

Yuang and Tien [45] propose an intelligent multiple access control system (IMACS) with facility for dynamic bandwidth allocation for wireless ATM multimedia networks. The IMACS consists of a multiple access controller (MACER), a traffic estimator and predictor (TEP), and an intelligent bandwidth allocator (IBA). MACER employs a hybrid-mode TDMA (time division multiple access) scheme with advantageous features of CDMA (code

division multiple access) and contention access based on a novel dynamic-tree-splitting collision resolution algorithm parameterized by an optimal splitting depth (SD). TEP periodically estimates the key Hurst parameter of available bit rate (ABR) self-similar traffic by wavelet analysis, and then predicts the mean and variance of subsequent frames using a six-layer neural fuzzy on-line traffic predictor (NFTP). Based on these predicted values, IBA performs efficient bandwidth allocation by determining the optimal SD, achieving satisfactory SCR (Signaling ContRol) blocking probability and ABR throughput requirements, while retaining maximal aggregate throughput. The NFTP algorithm achieves speed by learning in parallel the structure of the fuzzy *if-then* rules as well as the parameters for tuning the coefficients of the rules to input traffic dynamics.

For hierarchical cellular systems supporting multimedia services, Lo, Chang, and Shung [46] propose a neuro-fuzzy radio resources manager, which essentially contains a neural fuzzy channel allocation processor (NFCAP). The two layer architecture of the NFCAP includes a fuzzy cell selector (FCS) in the first layer and a neural fuzzy call-admission and rate controller (NFCRC) in the second layer. Using the user mobility, resource availabilities in both micro and macro cells, and handoff failure probabilities as input linguistic variables, the FCS comes up with a cell selection decision. The NFCRC then comes up with CAC and rate control decisions using the handoff probability, and the resource availability of the selected cell as input variables. Authors establish through simulations that their method enhances system utilization by 31.1% with a marginal 2% increase in handoff rate compared to overflow channel allocation scheme [47]. Compared to combined channel allocation [48] and fuzzy channel allocation control [49] schemes proposed by them earlier, the NFCAP is shown to provide 6.3 and 1.4% better system utilization and still achieve handoff rate reduction by 14.9 and 6.8%, respectively.

For third generation wireless multimedia networks demanding high throughput and QoS guarantees, Moustafa, Habib, and Naghshineh [50] propose an evolutionary computational model based wireless radio resource manager (RRM) that controls both the transmission power and the bit rate of the mobile devices cooperatively. Adaptive control of these parameters is achieved by the RRM on a continual basis by solving an optimization problem seeking to maximize a multi-modal objective function expressed as the sum of the total number users satisfying minimum signal quality requirements (assessed from their bit error rates), and the total reward for better utilization of resources, considering the relative reward values, for the corresponding users, for bandwidth utilization beyond their guaranteed minimum levels and frugal use of power. Experimental results indicate that their algorithm helps to reduce the infrastructure costs by requiring fewer base stations because of 70% more coverage on the average by each base station implementing the algorithm. Other benefits include significant decrease (40%) in call blocking rate, longer battery life of the mobile unit because of frugal use of power, and minimal interference among the users.

Motivated by the need for addressing the scarcity and large fluctuations in the availability of link bandwidth by the development of adaptive multimedia services, Fei, Wong, and Leung [51] propose a reinforcement learning approach for QoS provisioning by dynamic adjustment of the bandwidth allocations for individual ongoing calls. In this paper, the CAC and the dynamic bandwidth allocation problems are formulated as Markov decision processes (MDP) and solved using a form of real-time reinforcement learning scheme called Q-learning. In their formulation, whenever an event such as new or handoff call arrival, call termination, call handoff to neighboring cell occurs in a cell, an optimal policy, or equivalently an appropriate set of actions, e.g., acceptance/rejecion of a new/handoff call, bandwidth upgrading/downgrading of an ongoing call), is determined by maximization of the expected reward function subject to two QoS constraints- handoff dropping probability and average allocated bandwidth for a cell. The Q-learning approach permits efficient handling of the large state space, i.e., configuration of on-going calls of different types at a point in time) of the MDP problem without any prior knowledge of state transition probabilities. Simulation results indicate that this algorithm outperforms some traditional approaches [52,53] in bandwidth utilization and call drop reduction.

4 Multimedia Traffic Management and Congestion Control

Effective management of multimedia traffic is essential for guaranteed QoS. The traffic management entails a number of operations: (i) call admission control (CAC), (ii) traffic policing, (iii) traffic characterization and prediction, (iv) rate/flow control, (v) routing and link capacity assignment, and (vi) congestion control. Since CAC is a topic well addressed in the literature on CI methods for multimedia communications, we devoted a separate section in the beginning for this topic. For similar reasons, we will be dealing the traffic routing problem separately with particular emphasis on multicast routing in the following subsection. The remaining topics related to traffic management will be considered in this section. For a more comprehensive review of ATM traffic management, one may refer to the survey papers of Dodigeris and Develekos [54], and Sekercioglu, Pitsillides, and Vasilakos [55].

Call admission and resource allocation must necessarily be followed by policing of the multimedia network usage, and enforcement of proper usage so as to avert congestion and network delays. This process is also called usage parameter control (UPC) because it involves continuous monitoring of the sources for operation within the limitations of their respective CAC parameters negotiated during call setup phase. Next, traffic characterization and prediction is necessary for both CAC and flow control functions. Proper routing of traffic is essential for link capacity management, and hence congestion control. Finally, congestion control may also be done by rate control using a

feedback mechanism. Thus all the traffic management functions are closely inter-linked.

As in case of CAC, Hiramatsu [56] is one of the earliest researchers to employ neural networks for integrated ATM traffic control also. He proposes three levels of NNs: (i) cell transfer level NNs for call transmission pattern recognition, service class suggestion, and window size control, (ii) call level NNs for admission control of bursty calls and multi-level quality control, and (iii) network level NNs for optimal routing, link capacity assignment, and congestion control. For system efficiency, he proposes a two-phase training for the distributed system of NNs where separate training of individual NNs in the first phase is followed by the training of the whole system in the second phase. Addressing the link capacity assignment problem, he first estimates the CLR values for various links using a bank of three layer FFNNs with call generation rates and logical link capacities for the corresponding links as FFNN inputs. A neural network in the next higher level of hierarchy uses these estimated CLR values along with logical and physical link capacities as inputs, and performs multi-objective optimization by seeking to minimize maximum CLR value and maximize link utilization. The BP algorithm is used to train the neural network for estimation of CLR. For objective function optimization by the higher level network, Hiramatsu uses Matyas' random optimization method [57].

In [58], Tarraf, Habib, and Saadawi show how a comprehensive NN solution to traffic management problem in ATM multimedia networks can be worked out by integrating some of the earlier proposed NN-based methods for different aspects of traffic management. They divide the traffic management functional module into three submodules that operate at cell, call and network levels. The states of the buffers that maintain various types multimedia information together with the output of bandwidth assignment module at the UNIs (user-network interface), i.e., the access nodes to the network, provide the information required for processing at three control modules. The call level control function is implemented as a two-level hierarchy of feed-forward networks where two first level neural networks separately compute the service quality parameters such as call arrival rate, CLR, call rejection rate from the declared call parameters and history of the past observed status, and the statistical parameters of the aggregate link traffic from traffic measurements. The NN CAC at the second level aggregates the information from the first level neural networks and comes up with a decision to accept or reject a call. The authors propose that the traffic characterization and prediction at the cell level may be done using any of the earlier NN-based methods, e.g., [59, 60]) using the states of the UNI buffers as the NN inputs. The predicted traffic outputs from the NN then are used by another NN for policing as proposed in [61]. Finally, for the network level traffic control, the authors suggest implementing either of the two earlier proposed neural network congestion control mechanisms [62, 63].

Pitsillides, Sekercioglu, and Ramamurthy [64] use peak, minimum, and initial cell rates obtained by monitoring ABR queue lengths, additive increase rate, and control interval as inputs to their fuzzy congestion control system for estimation of flow rates which are provided as feedback to the traffic sources. Results of simulation experiment to compare their method with the EPRCA (Enhanced Proportional Rate Control Algorithm) [65] indicate that their algorithm fares better with respect to end-to-end delay, speed of transient response, and network utilization.

Lin et al. [66] propose a genetic algorithm based neural-fuzzy inference network for extraction of the features characterizing traffic at each node of a binary decision tree that is used in mixed scheduling of ATM traffic- a hybrid of rate monotonic and deadline driven approaches. The authors use simulations to show the effectiveness of the proposed GA based neural fuzzy network in learning optimal solutions compared to similar networks trained with the BP algorithm.

In [67], Chen et al. present an approach to traffic control that uses a fuzzy ARMAX (autoregressive moving-average model with auxiliary input) process for an effective modeling of nonlinear time-varying and time-delayed properties of multimedia traffic. In this model, traffic from controllable sources such as ABR traffic represents the fuzzy ARMA component and the uncontrollable traffic such as CBR (Constant Bit Rate), and VBR (Variable Bit Rate) traffic, is considered as external disturbance. Simulation results indicate that their method for fuzzy adaptive control of traffic flow using traffic prediction based on this model is superior to other competitive approaches with respect to cell loss rate and network utilization.

5 Routing and Multicast Routing

As indicated in the previous section, routing is a traffic management issue with impact on QoS at the network level. Multicast routing is a special case of routing of multimedia streams from a source to a number of destinations; it is pivotal to applications such as video conferencing, tele-classrooms, and video on demand. Needless to say, effective multicasting methods are also essential for QoS control.

Park and Lee [68] employ feedback neural networks for multimedia traffic routing. They solve the problem of maximizing the connected cross-points in a crossbar switch for a given traffic matrix subject the constraint that only one cross-point is permitted to be connected in each row or column of the switch, by casting the criterion function as an energy function that can be minimized by a Hopfield neural network.

Zhang and Leung [69] propose a novel genetic algorithm (GA) called orthogonal GA for multimedia multicast routing under delay constraints. In their GA formulation, a chromosome is a multicast tree represented as a binary string of size equal to the cardinality of the network link set. A value

of 1 (or zero) in the string indicates the presence (or absence) of the corresponding network link in the multicast tree. As a measure of quality of the multicast tree, the authors propose a fitness vector with two components: (i) cumulative path delays in excess of a configured threshold, and (ii) overall cost of the multicast tree. By lexicographic ordering of the vectors based on their component values, the multicast trees can be arranged in descending order of merit. An important aspect of the GA is an orthogonal crossover and mutation operation to generate j number of offsprings from n parents (the so called n-j crossover and mutation algorithm). Since the offsprings so generated may not necessarily be multicast trees (with connections from the source to destination nodes), the authors propose a check and repair operation also. Simulation results indicate that their orthogonal GA can find near optimal solutions for practical problem sizes.

In [70], Mao et al. present a genetic algorithmic approach to multi-path routing of multi description (actually double description) video in wireless ad hoc networks. In the multi-description multimedia encoding scheme that is gaining popularity of late, multiple streams corresponding to multiple equivalent descriptions of multimedia content generated from a source are transmitted to a destination which can use any subset of the source streams received to construct the original multimedia content with a quality commensurate with the cardinality of the subset used. The authors show that the multi-path routing problem is a cross-layer optimization problem where the average video distortion, i.e., an application layer performance metric, may be expressed as a function of the network layer performance metrics such as bandwidth, loss, and path correlation. Their final formulation turns out to be a problem of constrained minimization of average distortion of the received video expressed as a function of individual and joint probabilities for receiving the multiple descriptions, and the computable distortions for media reconstruction using the received streams. The constraints for their optimization are loop free paths and stable links. Due to the exponentially complex nature of the problem, the authors resort to genetic approach for the solution considering each candidate path constructed by random traversal from the source to destination as a chromosome and nodes (designated by their numbers and positioned in the same order as on the path) as genes. For the double description video problem, they use chromosome pairs as candidate solutions because two paths are required for transmitting the two descriptions. For cross over, two such path pairs are considered, one string from each pair is randomly chosen, and cross over is performed using the first common node in the chosen strings as the crossover point. Mutation on a chromosome (path) pair is similarly done by choosing one of the strings and a node in the string randomly, and reconstructing the partial path from that node to the destination node by using any constructive approach without repeating any nodes in the partial path from start node up to (but not including) the chosen node. The authors provide simulation results to demonstrate superior performance of their approach (in terms of the average Peak Signal to Noise Ratio of the reconstructed video)

over several other approaches including the 2-Shortest path [71] and Disjoint
Path-set Selection Protocol (DPSP) [72] algorithms.

In [73], Wang and Pavlou formulate group multicast content delivery in
multimedia networks as an integer programming problem to compute a set
of bandwidth constrained Steiner trees [74] with minimum overall bandwidth
consumption. Authors propose to represent the set of explicit Steiner trees
with shortest path trees (from the root node of the group to any receiver)
through intelligent configuration of a unified set of weights of the network
links. Accordingly, in their genetic algorithmic (GA) formulation, each chro-
mosome is represented by a link weight vector with the size equal to the
number of network links. Fitness of a chromosome is computed as a value
inversely proportional to the sum of the overall network load and excessive
bandwidth allocated to overloaded links. A fixed population size of 100 is cho-
sen, and GA evolution starts with an initial population of random vectors of
link wights in the range 1–64. In the crossover operation, the offsprings are
generated by taking a chromosome from both the top and the bottom fifty
(sorted with respect to the fitness values) and then choosing individual genes
for the offsprings from either parent with a predefined crossover probability.
To escape from local minima, two types of mutation (changing the weight of
a link to a random value) are used: (i) global mutation of every link with
a low mutation probability, and (ii) mutation of congested links. Results of
evaluation indicate that the proposed GA approach provides higher service
availability with significantly less bandwidth compared to the conventional
IP (Internet Protocol) approaches.

Neural network solutions to the allied problem of obtaining Steiner (mul-
ticast) trees from the network graph may be found in the literature. Gelenbe,
Ghanwani, and Srinivasan [75] demonstrate the use of random neural net-
works for substantial improvement in the quality of the Steiner trees that
may be obtained by using the best available heuristics such as the minimum
spanning tree and the average distance heuristics. In [76], Xia, Li, and Yen
propose a modified version of SOFM (self-organizing feature map) [7] for the
construction of balanced multicast trees.

6 Multimedia Composition, Encoding, Streaming, and Synchronization

Until now, our focus has been on control issues related to multimedia net-
working. In this section, we survey the sparse literature on the CI methods
that address pure communication issues related to multimedia data, such as
media streaming, synchronization, encoding, etc. In the following section, we
discuss a few CI-based multimedia services.

A cost effective (network bandwidth efficient) solution to multimedia con-
tent delivery in media browsing applications is low resolution content delivery
during navigation. The idea here is to permit the users to easily and quickly

preview media sequences at various resolutions and zoom in on the segments of their interest. Doulamis and Doulamis [77] propose an optimal content-based media decomposition (composition) scheme for such an interactive navigation. Though their proposal is for video navigation, the scheme can be extended to the generic multimedia case. In their scheme, a set of representative shots is initially extracted from the sequence to form a coarse description of the visual content. The remaining shots are classified into one or the other representative shot class types. The content of each shot is similarly decomposed into representative frames (frame classes) characterized by global descriptors such as color, texture, motion parameters, and object (region) descriptors such as size and location. The other objects in the shot are classified into one or the other of the frame classes. The video decomposition problem is then posed as a problem of optimally selecting representative shots (frames) so as to minimize the aggregate correlation measure among the shots (frames) of the same class. In view of the exponential complexity of the search for optimal solution, the authors use a genetic search using a binary string representation for denoting the presence or absence of the shots (frames) in the sequence (shot) in the representative classes. The scheme is shown to offer a significant reduction (85 to 1) in the transmitted information compared to the traditional sequential video scanning.

In [78], Su and Wah propose an NN-based approach to compensation of compression losses in multi-description video streaming. To facilitate realtime playback, a three-layer FFNN in their system is trained in advance by the BPL algorithm using pixels from deinterleaved and decompressed frames as FFNN inputs, and those taken from the original frames (before compression) as desired outputs.

Bojkovic and Milovanovic [79] propose a motion-compensated discrete cosine transform (MC-DCT) based multimedia coding scheme that optimally allocates more bits to regions of interest (ROI) compared to non-ROI image areas. Identification of ROIs is done by a two-layer neural network with the FFNN in the first layer for generation of the segmentation mask using the features extracted from each image block, and the FFNN in the second layer for improving the obtained segmentation by exploiting object continuity in the segmentation mask provided by the first network and additional features. Authors indicate that their approach achieves better visual quality of images along with signal-to-noise ratio improvements compared to the standard MPEG (Moving Picture Experts Group) MC-DCT encoders.

Automatic quantitative assessment of the quality of video streams over packet networks is an important problem in multimedia engineering. Packet video quality assessment is a difficult problem that depends on a number of parameters such as the source bit rate, the encoded frame type, the frame rate at the source, the packet loss rate in the network, *etc.* A method for such an assessment, however, facilitates development of control mechanisms to deliver the best possible video quality given the current network situation. In [80], Mohamed and Rubino propose the use of Gelenbe's random neural

network (RNN) model [6]. Mohamed and Rubino show the results obtained using RNNs are well correlated with the results of subjective analysis using our human perceptual system. Cramer, Gelenbe, and Gelenbe use an RNN-based scheme for video compression [81] and indicate that it is several times faster than H.261 and MPEG based compression schemes.

Addressing the problem of integrating user preferences with network QoS parameters for streaming of the multimedia content, Ghinea and Magoulas [82] suggest the use of an adaptable protocol stack that can be dynamically configured with micro-protocols for various micro-operations involved in streaming such as sequence/flow control, acknowledgement, and error checking/correction coding. Then they formulate the protocol configuration as a multi-criteria decision making problem (to determine streaming priorities) that is solved by a fuzzy programming approach to resolve any inconsistencies between the user and the network considerations.

Synchronized presentation of multimedia is an important aspect of nearly all multimedia applications. In [83], Zhou and Murata adopt a CI approach to the media synchronization problem, and propose a fuzzy timing Petri Net model (FTPNM) for handling uncertain or fuzzy temporal requirements, such as imprecisely known or unspecified durations. The model facilitates both intra-stream and inter-stream synchronization with guaranteed satisfaction of QoS requirements such as maximum tolerable jitters (temporal deviations) of individual streams, and maximum tolerable skew between media, by optimal placement of synchronization points using the possibility distributions of the QoS parameters obtained from the model.

Considering the need for lightweight synchronization protocols that can readily adapt to the non-stationary workload of the browsing process and changing network configurations, Ali, Ghafoor, and Lee [84] propose a neuro-fuzzy framework for media synchronization on the web. In their scheme, each multimedia object i.e., video, voice, etc.) is segmented into an atomic unit of synchronization (AUS). With this, the media synchronization turns out to be a problem of appropriately scheduling the AUS despatches by web servers. The authors observe that this, in turn, is a multi-criteria scheduling problem with objectives to: (i) minimize tardy (deadline missing) AUSs, (ii) complete the transmission of bigger AUSs as close to their deadline as possible, and (iii) minimize dropping of AUSs in the event of severe resource constraints. This problem being NP-hard, the solution is approached through a neuro-fuzzy scheduler (NFS) that makes an intelligent compromise among the multiple objectives by properly combining a number of heuristic scheduling algorithms proposed by the authors. The NFS comes up with scheduling decisions taking the workload parameters and system state parameters as inputs. A two phase learning scheme is used in the NFS with self-organized learning in phase-I to construct the presence of rules and locate initial membership functions for the rules, and supervised learning in phase-II to optimally adjust the membership functions for the desired outputs. Simulation studies for a comparative assessment of the proposed method against several known

heuristic methods and a branch and bound algorithm demonstrate superior adaptability of the method under varying workload conditions.

One of the rare applications of rough set theory (RST) to multimedia is due to Jeon, Kim, and Jeong [85]. The authors propose a novel method (with attribute reduction by application of RST) for video deinterlacing. In their method, they estimate the missing pixels by employing, on a pixel-by-pixel basis, one of the following four earlier proposed deinterlacing methods: BOB [86], WEAVE [86], STELA [87], and FDOI [87]. Their deinterlacing approach uses four parameters: TD, SD, TMDW and SMDW. The first two parameters refer to the temporal, and spatial differences, respectively, between two pixels across the missing pixel, and the remaining two refer to temporal and spatial entropy parameters described in [87]. Using six video sequences as the training data, the authors first construct a fuzzy decision table that maps each set of the fuzzy values (small, medium, and high) of the attributes derived from the above parameters onto a decision on the choice of an algorithm from the four mentioned above. The RST is then used for finding the core attributes, and eliminating superfluous attributes by constructing the upper and lower approximation sets of the target algorithms for the subsets of the attributes. With experimentation on a different set of six standard video sequences, the authors establish the superior performance of their method over a number of methods presented in the literature.

7 Multimedia Services and Servers

Prediction of user mobility profile in wireless multimedia communication systems is an essential support service for effective resources utilization under QoS constraints. Shen, Mark, and Ye [88] propose an adaptive fuzzy inference approach to user mobility prediction in a wireless network operating in Frequency Division Duplex (FDD) mode with DS/CDMA (Direct Spread-spectrum CDMA) protocol. The essential components of their system are a fuzzy estimator (FE) and a recursive least squares (RLS) predictor. The FE takes in as input the strength of the pilot signal from the mobile user, and predicts the probability of the user being in a particular cell using a rule base that takes into account imprecision in measurements, and shadow effects. The RLS predictor then improves upon the estimate obtained from FE using the previous few values of the mobile position.

Addressing the problem of placing multiple copies of videos on different servers in a multi-server video on demand system, Tang et al. [89] propose a hybrid genetic algorithm to determine the optimal video placement that minimizes batching interval and server capacity usage while satisfying pre-specified requirement on blocking probability and individual server capacities. A chromosome in their GA formulation is an integer string with length equal to the number of videos where each integer represents the number of copies of a particular video. They use a fitness vector with two components: (i) the

blocking probability (computed as $\sum_j q_j B_{q_j}$ where q_j is the portion of the effective traffic allocated to a server (j), and B_{q_j} is the blocking probability for the server j that is computable using Erlang B formula [90] given the number of multicast streams j is handling), and (ii) the total capacity usage. For ranking the chromosomes in a population, a multi-objective pareto ranking scheme [91] is used. Offsprings in the GA are generated by multi-point crossovers and mutation. The exact size of the population used in their experimentation is not explicitly stated in the paper. The experimental results indicate that the proposed algorithm converges to the best value on blocking probability at around 1000 generations, and the best value on server capacity usage in less than 4000 generations.

In [92], Ali, Lee, and Ghafoor propose a design of multimedia web server using a neuro-fuzzy framework. The crux of their design is a neuro-fuzzy scheduler (NFS) for synchronized delivery of multimedia documents. In the previous section, an overview of this scheduler has already been presented in the context of media synchronization problem using a more comprehensive journal publication by the same authors [84].

8 Challenges and Future Directions

Even though many CI-based approaches are being proposed for various applications in multimedia networking and communications, their impact is mostly confined to academic circles. These methods are yet to find wide acceptance in industrial circles (possibly except in Japan), and get incorporated in many industrial products. This trend is also evident from the very small number of industrial patents in this direction. Hence, the main challenge of CI researchers is to provide the industry leaders a convincing demonstration of the superiority of their approaches over the traditional methods. Another challenge is to develop methods compatible with existing standards, and new standards that facilitate CI-based implementations. Furthermore, since success of the fuzzy methods depends upon the compilation of a good knowledge base, gathering of rules of inference from experts remains a challenge for fuzzy systems designers. Similarly, development of new types of neural networks, their training algorithms, novel GAs preferably with parameters, e.g., population size, crossover and mutation rates) self-configurable by means of problem heuristics, and hybrid CI methods immensely suitable for the application problem at hand is always a challenge for the CI researchers.

Most of the current literature on CI based methods for multimedia communications addresses the ATM network issues. A few papers deal with wireless multimedia. With the current trend towards IP based multimedia communications in both wired-line and 3GB (third generation and beyond) mobile wireless networks, there is a need to develop CI-based methods for IP-based network communications. Further, as is obvious from relatively much smaller coverage on multimedia communication aspects compared to that on network

control aspects in the current article, pure communication issues in multimedia and mobile multimedia are not that well addressed by the CI methods in the current literature. The same applies to multimedia services and on-demand services. New on-demand services may be designed by employing either new or existing CI based methods. Hence, exploration of CI methods for new services and communication methods will be a fruitful direction of research in the future. Specific problems that have already been identified by the editors of this volume in this context are: (i) multimedia semantic characteristics in wireless, mobile, and ubiquitous environments, (ii) extraction and usage of semantic information in wireless and mobile environments, (iii) multimedia retrieval in wireless and mobile networks, (iv) P2P multimedia streaming in wireless and mobile networks, and (v) performance evaluation of mobile multimedia services. Finally, from the perspective of the specific CI approaches that need to be applied, explorations into possible applications of rough sets, and hybrids of neural, rough set, and fuzzy approaches to multimedia could lead to new and interesting avenues of research.

References

1. Rumelhart D E, McClelland J L (1986) Parallel Distributed Processing: Explorations in the Microstructure of Cognition, volume 1. MIT Press, Massachusetts
2. Almeida L B (1987) Proceedings of the IEEE First International Conference on Neural Networks 11:609–618
3. Pineda F J (1987) Phys Rev Let 19:2229–2232
4. Hopfield J J (1982) Proceedings of the National Academy of Sciences of the USA 79(8): 2554–2558
5. Binder K, Ising Model (2001) SpringerLink Encyclopaedia of Mathematics, Springer
6. Gelenbe E (1989) Neural Computing 1:502–511
7. Kohonen T (1997) Self-organizing maps, 2nd Edition, Springer Verlag, Berlin Heidelberg New York
8. Sutton R S, Barto A G (1998) Reinforcement Learning: An Introduction. MIT Press, Massachusetts
9. Puterman M L (1994) Markov Decision Processes. Wiley, New York
10. Zadeh L A (1965) Information and Control 8: 338–353
11. Mamdami E H (1974) Proceedings of the Institute of Electrical Engineers 121 (12):1585–1588
12. Pawlak Z (1991) Rough Sets: Theoretical Aspects of Reasoning About Data. Kluwer, Dordrecht
13. Dubois D (1990) International Journal of General Systems 17:191–209
14. Stefanowski J (1998) On rough set based approaches to induction of decision rules. In: Polkowski L, Skowron A (eds.) Rough Sets in Knowledge Discovery 1: Methodology and Applications: 500–529, Physica-Verlag, Heidelberg
15. Ziarko W (1998) Rough sets as a methodology for data mining. In: Polkowski L, Skowron A (eds.) Rough Sets in Knowledge Discovery 1: Methodology and Applications: 554–576, Physica-Verlag, Heidelberg

16. Fogel L J, Owens A J, Walsh M J (1966) Artificial Intelligence Through Simulated Evolution. Wiley, New York
17. Holland J H (1975) Adaptation in natural and artificial systems. University of Michigan Press, Ann Arbor
18. Rechenberg I (1973) Evolutionstrategie: Optimierung Technisher Systeme nach Prinzipien des Biologischen Evolution. Fromman-Hozlboog Verlag, Stuttgart
19. Schwefel H -P (1981) Numerical Optimization of Computer Models. John Wiley and Sons, New-York
20. Koza J R (1992) Genetic Programming: On the Programming of Computers by means of Natural Evolution. MIT Press, Massachusetts
21. Hiramatsu A (1990) IEEE Transactions on Neural Networks 1(1):122–130
22. Hiramatsu A (1995) IEEE Communications Magazine 33(10):58, 63–67
23. Youssef S A, Habib I W, Saadawi T N (1997) IEEE Journal on Selected Areas in Communication (Special Issue on Computational and Intelligent Communication) 15(2):191–199
24. Guerin R, Ahmadi H, Naghshineh M (1991) IEEE Journal on Selected Areas in Communication 9(7):968–981
25. Vakil F (1993) Proceedings of the IEEE GLOBECOM Conference 1993 (1):406–416
26. Uehara K, Hirota K (1997) IEEE Journal on Selected Areas in Communication (Special Issue on Computational and Intelligent Communication) 15(2):179–190
27. Bensaou B, Lam S T C, Chu H -W, Tsang D H K (1997) IEEE/ACM Transactions on Networking 5(4):572–584
28. Klir G J, Yuan B (1995) Fuzzy Sets and Fuzzy Logic: Theory and Applications. Prentice-Hall, New York
29. Ren Q, Ramamurthy G (2000) IEEE Journal on Selected Areas in Communication 18(2):184–196
30. Liang Q, Karnik N N, Mendel J M (2000) IEEE Transactions on Systems, Man, And Cybernetics–Part C: Applications And Reviews 30(3):329–339
31. Cheng R -G, Chang C -J, Lin L -F (1999) IEEE/ACM Transactions on Networking 7 (1):111–121
32. Chang C -J, Cheng R -G, Lu K -R, Lee H -Y (2000) Neural Fuzzy Connection Admission Controller and Method in a Node of an Asynchronous Mode Transfer (ATM) Network. US Patent# 6067287
33. Cheng R -G, Chang C -J (1996) IEEE/ACM Transactions on Networking 4(3):460–469
34. Kesidis G, Walrand J, Chang C -S (1993) IEEE/ACM Transactions on Networking 1(4):424–428
35. Cheng R -G, Chang C -J (1997) Proceedings of IEE Communications 144(2):93–98
36. Chatovich A, Oktug S, and Dundar G (2001) Computer Communications 24:1031–1044
37. Berenji H R, Khedkar P (1992) IEEE Transactions on Neural Networks 3(5):724–740
38. Shen S, Chung-Ju C, ChingYao H, Qi B (2004) IEEE Transactions on Wireless Communications 3(5):1810–1821
39. Ahn C W, Ramakrishna R S (2004) IEEE Transactions on Vehicular Technology 53 (1):106–117
40. Senouci S -M, Beylot A -L, Pujolle G (2004) International Journal on Network Management 14:89–103

41. Ye J, Shen X(S), Mark J W (2005) IEEE Transactions On Mobile Computing 4(2):129–141
42. Huang C Y, Yates R D (1996) Proceedings IEEE Vehicular Technology Conference '96:1665–1669
43. Sun S, Krzymien W A (1998) Proceedings of the IEEE Vehicular Technology Conference '98:218–223
44. Sherif M R, Habib I W, Nagshineh M, Kermani P (2000) IEEE Journal on Selected Areas in Communications 18(2):268–282
45. Yuang M C, Tien P L (2000) IEEE Journal on Selected Areas in Communications 18(9):1658–1669
46. Lo K -R, Chang C -J, Shung C B (2003) IEEE Transactions On Vehicular Technology 52 (5):1196–1206
47. Rappaport S S, Hu L R (1994) Proceedings of the IEEE 82(9):1383–1397
48. Lo K -R, Chang C -J, Chang C, Shung C B (1998) Computer Communications 21(13):1143–1152
49. Lo K -R, Chang C -J, Chang C, Shung C B (2000) IEEE Transactions on Vehicular Technology 49(5):1588–1598
50. Moustafa M, Habib I, Naghshineh M N (2004) IEEE Transactions on Wireless Communications 3(6):2385–2395
51. Fei Y, Wong V W S, Leung V C M (2006) Mobile Networks and Applications 11:101–110
52. Hong D, Rappaport S S (1986) IEEE Transactions on Vehicular Technology 35(3):77–92
53. Talukdar A K, Badrinath B R, Acharya A (1998) Proceedings ACM/IEEE MobiCom' 98:169–180
54. Douligeris C, Develekos G (1997) IEEE Communications Magazine 35(5): 154–162
55. Sekercioglu A, Pitsillides A, Vasilakos A (2001) Soft Computing Journal 5(4):257–263
56. Hiramatsu A (1991) IEEE Journal on Selected Areas in Communications 9(7):1131–1138
57. Matyas J (1965) Automation and Remote Control 26:246–253
58. Tarraf A A, Habib I W, Saadawi T N (1995) IEEE Communications Magazine 33 10):76–82
59. Tarraf A A, Habib I W, Saadawi T N (1993) Proceedings of the IEEE GLOBECOM '93(2):996–1000
60. Neves J E, de Almeida L B, Leitao M J (1994) Proceedings of the IEEE ICC '94(2):769–773
61. Tarraf A A, Habib I W, Saadawi T N (1994) IEEE Journal on Selected Areas in Communications 12(6):1088–1096
62. Tarraf A A, Habib I W, Saadawi T N (1995) Proceedings of the IEEE ICC '95(1):206–210
63. Liu Y, Douligeris C (1995) Proceedings of the IEEE GLOBECOM '95(1):291–295
64. Pitsillides A, Sekercioglu Y A, Ramamurthy G (1997) IEEE Journal on Selected Areas in Communications 15(2):209–225
65. Roberts L (1994) Enhanced PRCA (proportional rate-control algorithm). Technical Report AF-TM 94-0735R1

66. Lin C -T, Chung I -F, Pu H -C, Lee T -H, Jyh-Yeong Chang J -Y (2003) IEEE Transactions on Systems, Man, and Cybernetics-Part B: Cybernetics 32(6):832–845
67. Chen B -S, Yang Y -S, Lee B -K, Member, Lee T -H (2003) IEEE Transactions on Fuzzy Systems 11(4):568–581
68. Park Y -K, Lee G (1995) IEEE Communications Magazine 33(10):68–74
69. Zhang Q, Leung Y -W (1999) IEEE Transactions on Evolutionary Computation 3(1):53–62
70. Mao S, Hou Y T, Cheng X, Sherali H D, Midkiff S F, Zhang Y -Q (2006) IEEE Transactions On Multimedia 8(5):1063–1074
71. Eppstein D (1999) SIAM Journal of Computing 28(2):652–673
72. Papadimitratos P, Haas Z, Sirer E (2002) Proceedings of ACM Mobihoc:1–11
73. Wang N, Pavlou G (2007) IEEE Transactions on Multimedia 9 (3):619–628
74. Hwang F K, Richards D S, Winter P (1992) The Steiner Tree Problem. Elsevier, North-Holland.
75. Gelenbe E, Ghanwani A, Srinivasan V (1997) IEEE Journal on Selected Areas in Communications 15(2):147–155
76. Xia Z, Li P, Yen I-L (2004) Proceedings of the 18th International Parallel and Distributed Processing Symposium:54–63
77. Doulamis A D, Doulamis N D (2004) IEEE Transactions on Circuits and Systems for Video Technology 14(6):757–775
78. Su X, Wah B W (2001) IEEE Transactions on Multimedia 3(1):123–131
79. Bojkovic Z, Milovanovic D (2004) Seventh Seminar on Neural Network Applications in Electrical Engineering:67–71
80. Mohamed S, Rubino G (2002) IEEE Transactions On Circuits And Systems For Video Technology 12(12):1071–1083
81. Cramer C, Gelenbe E, Gelenbe P (1998) IEEE Potentials 17(1):29–33
82. Ghinea G, Magoulas G D (2005) IEEE Transactions on Multimedia 7(6):1047–1053
83. Zhou Y, Murata T (1998) IEEE International Conference on Systems, Man, and Cybernetics '98(1):244–249
84. Ali Z, Ghafoor A, Lee C S G (2000) IEEE Journal on Selected Areas in Communications 18(2):168–183
85. Jeon G, Kim D, Jeong J (2006) IEEE Transactions on Consumer Electronics 52 (4):1348–1355
86. Haan G D, Bellers E B (1998) Proceedings of the IEEE 86(9):1839–1857
87. Jeon G, Jeong J (2006) IEEE Transactions on Consumer Electronics 52(3):1013–1020
88. Shen X, Mark J W, Ye J (2000) Wireless Networks 6:363–374
89. Tang W K S, Wong E W M, Chan S, Ko K -T (2004) IEEE Transactions on Broadcasting 50(1):16–25 D.
90. Bertsekas D, Gallager R (1992) Data Networks. Prentice-Hall, New York, p. 179
91. Fonseca C M, Fleming P J (1998) IEEE Tranactions on Systems, Man, and Cybernetics Part A: Systems and Humans 28(1):26–37
92. Ali Z, Lee C S G, Ghafoor A (2000) IEEE International Conference on Fuzzy Systems 9 (1):510–515