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# A survey of fuzzy logic monitoring and control utilisation in medicine

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**Abstract**

Intelligent systems have appeared in many technical areas, such as consumer electronics, robotics and industrial control systems. Many of these intelligent systems are based on fuzzy control strategies which describe complex systems mathematical models in terms of linguistic rules. Since the 1980s new techniques have appeared from which fuzzy logic has been applied extensively in medical systems. The justification for such intelligent systems driven solutions is that biological systems are so complex that the development of computerised systems within such environments is not always a straightforward exercise. In practice, a precise model may not exist for biological systems or it may be too difficult to model. In most cases fuzzy logic is considered to be an ideal tool as human minds work from approximate data, extract meaningful information and produce crisp solutions. This paper surveys the utilisation of fuzzy logic control and monitoring in medical sciences with an analysis of its possible future penetration. © 2001 Elsevier Science B.V. All rights reserved.

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## 1. Introduction

The last couple of decades have witnessed significant developments in control systems theory. In the meantime, developments in electronics and computers have resulted in many application areas of control systems theory. Although medicine is a science which is not related to control engineering, it is being affected to such an extent that it is now possible to use available control techniques for on-line devices, especially during surgical operations

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and in intensive care units. The current application areas of control engineering in medicine constitute a wide spectrum ranging from simple dosage prescription schemes to highly sophisticated adaptive controllers.

In medicine, the principle of "measuring everything measurable and trying to make measurable what has not been measurable so far" (Galileo) is still practised, nevertheless, some fundamental limitations have already being recognised. Real world knowledge is characterised by incompleteness, inaccuracy, and inconsistency. Fuzzy set theory, which was developed by Zadeh [73], makes it possible to define inexact medical entities as fuzzy sets. It provides an excellent approach for approximating medical text. Furthermore, fuzzy logic provides reasoning methods for approximate inference.

This paper presents a survey of the utilisation of fuzzy logic control and monitoring in medicine based on National Library of Medicine (USA) and INSPEC. The word "fuzzy" was used with "control or monitoring or treatment or therapy or planning". The survey uses longitudinal rubric (time scale) as well as transversal rubric (intellectual connectivity of medical disciplines).

## 2. Fuzzy control and monitoring in medical fields

Imprecisely defined classes play an important role in human thinking. Fuzzy set theory derives from the fact that most natural classes and concepts are fuzzy rather than of crisp nature. On the other hand, people can approximate well enough to perform many desired tasks. The fact is that they summarise from massive information inputs and still function effectively. For complex systems, fuzzy logic is quite suitable because of its tolerance to some imprecision. In the following sections a brief description is given of the key contributions that fuzzy control, estimation, and measurements technology have made in each of the topics identified in the medical literature search.

This survey was conducted in order to establish a roadmap that is able to forecast the future developments of fuzzy control and monitoring technology in medicine and healthcare. The medical activities have been divided into seven fields, each of which is further divided into special applications that belong to each field. A total of 34 sectors were defined. These sectors are organised in a hierarchical scheme according to the medical procedures. This means that significant methodologies relationships and demands can be correlated. This scheme substantiates the hypothesis that a successful application in one sector should lead to a successful application in the neighbouring sector.

### *2.1. Conservative disciplines*

Conservative medicine can be classified into the following disciplines: internal medicine, cardiology, intensive care, paediatry, endocrinology, oncology gerontology, and general practice. The literature search only found limited application of fuzzy control mostly in general practice and cardiology. Fuzzy logic is utilised for improved monitoring in pre-term infants [70]. A self-organising anomaly detection system for an electrocardiogram (ECG) using a fuzzy logic reasoning method was also developed [2].

### 2.2. Invasive medicine

The invasive medicine field involves surgery, orthopaedics, anaesthesia, and artificial organs. The field of surgery is very wide as many factors contribute to it such as diagnostics, image processing, patho-physiological reasoning, and anaesthesia control. In anaesthesia, many applications have been reported in the use of fuzzy logic to control drug infusion for maintaining adequate levels of anaesthesia, muscle relaxation, and patient monitoring and alarm. In the field of orthopaedics, there has been no reported application of fuzzy control.

The field of anaesthesia is where most of the applications of fuzzy control have been reported. It involves monitoring the patient vital parameters and controlling the drug infusion to maintain the anaesthetic level constant. It includes depth of anaesthesia [1], muscle relaxation [34,69], hypertension during anaesthesia [51], arterial pressure control [74] and mechanical ventilation during anaesthesia [58], and post-operative control of blood pressure [72].

Different methods have been used which utilise fuzzy logic, the first being a real-time expert system for advice and control (RESAC) based on fuzzy logic reasoning [22]. Later examples involve a basic fuzzy logic controller [34], self-organising fuzzy logic controller [32], and hierarchical systems [56]. Recent work in anaesthesia monitoring and control concentrated on a multi-sensor fusion system using cardiovascular indicators, such as systolic arterial pressure (SAP), heart rate (HR) and audio evoked response signals (AER) [36]. The two measures are fused together to obtain a final measure of depth of anaesthesia (DOA). Fuzzy rule-base classifiers were designed and included in a closed loop control system to determine the target propofol concentrations in the blood and hence the drug administration regime.

Most of the fuzzy logic control applications in the field of artificial organs are concerned with artificial hearts. A fuzzy controller has been implemented for adaptation of the heart pump rate to body perfusion demand by pump chamber filling detection [28]. Another more advanced system, which is based on neural and fuzzy controller for artificial heart, was developed by Lee et al. [37]. Future prospects for cardiac assisted patients involving fuzzy logic was described by Mussivand [45].

### 2.3. Regionally defined medical disciplines

There are different fields which belong to regionally defined medical disciplines: gynaecology, dermatology, dental, ophthalmology, otology, rhinology, laryngology and urology. Although there are many application fields, the literature search has only resulted in a single application of fuzzy inference to dental medicine. Although the application is not directly related to control, it utilises fuzzy inference for personal identification/sex determination from teeth [62].

### 2.4. Neuromedicine

Neurology, psychology, and psychiatry are the sub-subjects of the neuromedicine field. The neurology sector did not score literature on fuzzy control. In psychology, there has been modelling of the functional status of a human operator based on fuzzy logic which is used to predict and evaluate the operator's behaviour [7]. Also, fuzzy logic was used to analyse the effect of face expression on speech perception in direct communication [41]. The prediction of patient response to new pharmacotherapies for alcohol dependence has been measured using fuzzy logic since it has been not successful using standard statistical techniques [46].

In the field of psychiatry, a complex psychiatric computer expert system, including functions that help the physicians and the hospital staff in the administrative, diagnostic, therapeutic, statistical, and scientific work has been developed [30]. Recent work by Toglia and co-workers [64] showed results of experiments which highlighted the persistence of the ''false memory effect''. Analysis of such results revealed that semantic processing was the primary factor, and interpretations, which rely on fuzzy theory, were proposed.

### *2.5. Image and signal processing*

Image and signal processing are mainly concerned with signal processing, radiation medicine, and radiology. The application of fuzzy control is divided into two sections, control and monitoring. Most of the applications have been concerned with signal processing. The first application is a combined fuzzy monitoring and control of the electrical and chemical responses of nerve fibres [3]. Another application is the automation of matrix-assisted laser desorption/ionization mass spectrometry using fuzzy logic feedback control [25]. Fuzzy feedback control was implemented for artificial ventilation of lungs [66]. On the monitoring side, fuzzy signal processing has been implemented in many applications such as sleep monitoring [18], monitoring of pre-term infant [70], clinical monitoring of disease progression [60], and analysis of eyes movements [4]. Recently, Ogawa and co-workers [49] proposed a three dimensional ultrasonic imaging and digital processing method for extracting and constructing a breast tumour. The automated system, which is intended for the diagnosis of breast tumours, uses fuzzy reasoning with membership functions defined as Rician distribution functions.

Radiation medicine is mainly concerned with tumour monitoring and quantification. Fuzzy clustering is used to analyse magnetic images of tumour response to therapy [65,67]. In another application, high-energy radiotherapic images with poor-quality, have used a fuzzy image enhancing process [31]. Lastly, a two-dimensional image restoration technique using fuzzy logic was developed for diagnostic and treatment planning in radiation therapy [11].

### *2.6. Laboratory*

The only direct application of fuzzy control strategies was the application of pH-state to fed-batch cultivation of genetically engineered *Escherichia coli*. The control of the substrate concentration at an appropriate level was sought in order to avoid the accumulation of acetate, thereby elevating the expression level of plasmid-encoded protein [26].

Analysis and interpretation of laboratory data sets was the other indirect application of fuzzy logic. Two typical applications are: interpretation of patho-physiology by laboratory data [59], and analysis of the variations of clinical test data on fasting therapy using a fuzzy similarity dendrogram [50]. Garibaldi and Ifeachor [17] describe a fuzzy expert system for the blood analysis of the umbilical cord of infants immediately after delivery. The system hence built has the ability to provide valuable information on the health of the newly born infant and guide requirements for neonatal care. Fuzzy logic is used as a basis for this work due to the errors contained in the collected data which render other techniques unable to interpret the results accurately.

### 2.7. Basic science

Basic science consists of different categories: medical information, anatomy, pathology, forensic medicine, genetics, physiology, pharmacology, and education. The use of fuzzy logic in medical informatics began in the early 1970s. Recent work on fuzzy controllers is more concerned with stability, self-organising, and synergies with other computing techniques such as neural networks and genetic algorithms. Management and retrieval of information using fuzzy logic is one of the possible application discussed by Chiodo et al. [13]. Recently, a decision support system running across the World-Wide Web was designed by MacCall and Petrovski [42]. The client server contains a database of treatment information with optimisation possibilities using genetic algorithms; the system being currently under trial in the United Kingdom. More recently, Sadegh-Zadeh [52,53] devoted two papers to the development of a fuzzy theory for health, illness, and disease; an extensional-recursive scheme for defining the controversial notion of disease is proposed that also supports a concept of fuzzy disease. A sketch is given of the ball theory of disease.

In the fields of anatomy, pathology, forensic medicine and genetics, there are many application of fuzzy logic mostly based on image analysis and fuzzy clustering. In pathology, an expert system was used based on fuzzy logic for reasoning with uncertainties in selecting treatment strategy suitability [21]. In forensic medicine, fuzzy logic was used to personal identification (sex determination) from teeth [62]. In genetics, fuzzy logic has been used to develop control strategies for the application of pH-state to fed-batch cultivation of genetically engineered *Escherichia coli* [26]. Recent work on genomes by Sadegh-Zadeh [54] showed that genetic information in particular and genetics in general become amenable to fuzzy theory, geometry, and topology. This research work comes at a crucial time as more and more researchers are anxious to see this part of science develop rapidly and successfully.

In pharmacology and biochemistry, fuzzy logic prediction was used for the rodent carcinogenicity of organic compounds using a fuzzy adaptive least-squares method [44]. In education, the use of fuzzy logic has different facets. Fuzzy mathematics was utilised for evaluating the teaching of students in a clinical setting [12]. Evaluation of the self-taught ability of nursing administrators with fuzzy medicine was also reported [68].

### 2.8. Healthcare

There has been a growing interest in healthcare among many people. Some topics related to healthcare are: drinking water quality, driving fatigue, health risks in work environment [19], and healthcare organisations. For instance, Yamaguchi and co-workers [71] developed a fuzzy-based workload control system based on principal component analysis of heart rate and myoelectric signals. Such as system proved efficient in reducing fatigue in terms of cardiovascular activity, respiration and muscles in old adults.

During the management process in health organisations, certain situations can arise when data necessary for decision-making is in fuzzy form. As an example, the problem of resource allocation among consulting rooms in the outpatient division of one hospital in Tbilisi was chosen. The aim is to minimise patients' queues as well as physicians' idle time [27].

## 3. Fuzzy control techniques

Various therapeutic situations are related to control problems. Although the early medical systems appeared at the same time as the article by Zadeh [73], there has been little communication between the research fields, but recently this has changed due to the developments in computer systems, and rapid development of the literature searching methods motivated by the Internet and the World-Wide Web. Many systems are being developed which utilise fuzzy logic and fuzzy set theory.

### *3.1. Basic controllers*

Fuzzy rule-based systems include many aspects of fuzzified values, such as the rules antecedents and consequence. The rules structure are usually of the form IF ... THEN. In its basic form this type of control is equivalent linguistically to a PI controller, and depending on the output, whether it is incremental or absolute, the controller is known as PI or PD respectively. An example of such a rule is IF "*blood pressure is above the target and decreasing slowly*", THEN "*reduce drug infusion*". A more sophisticated structure can be a PID controller, where the input, its derivative, and integral are considered as three inputs. The rules are composed either from the expert (anaesthetists) or crafted by hand depending on the experience of the programmer. This includes tuning the membership functions in terms of the shape, width and position. This type of controller is widely used and is the most applicable control type in anaesthesia [16].

### *3.2. Rule-based open-loop systems*

Deterministic open-loop fuzzy control approaches have been proposed in many applications. Generally, in an open-loop configuration, it is assumed that the pharmacokinetics relationships can be modelled exactly by a linear system with known parameters. Open-loop fuzzy control is based on a different approach. Rather than assuming the patient model is known, the physiological behaviour is modelled using control rules and actions. Most of the controllers are advisory systems. In healthcare, the "heaviness" is defined by means of fuzzy sets for advising workers how heavy their workload is [19]. Also, fuzzy control was used to develop a computer-based system for control of oxygen delivery to ventilated infants [61]. An open-loop system for treatment of diabetic out-patients was developed for calculating the insulin dose [29,57]. Advisory expert systems can also be considered as open-loop controllers for advising on drug administration in general anaesthesia [22].

### *3.3. Rule-based closed-loop systems*

Closed-loop control in medicine emerged as a serious contender for many forms of control in late 1970s. It was pioneered by Sheppard et al. [55] and Asbury et al. [5] when they demonstrated through clinical experiments that this form of control is safe, effective and in many cases better than manual control. Closed-loop control methods can be divided into two groups: adaptive and non-adaptive. In a following section, more details are given of the different types of closed-loop controllers.

### *3.4. Self-learning systems*

Self-learning systems are concerned with the control of systems with unknown or time varying structure or parameters. The self-organising fuzzy logic controller has the ability to realise adaptation by building its fuzzy rules on-line as it controls the process, altering and adding as many rules as it judges necessary from off-line criteria. This approach has many successful applications in the control of muscle relaxation [32], and simultaneous control of blood pressure and muscle relaxation [38].

### *3.5. Model based and adaptive systems*

Model-based and adaptive systems are most successful when a physician plays a part in the closed-loop. The adaptive scheme plays an important role in adapting the controller to changes in the process (patient) and its disturbances. Fuzzy modelling and control are often based on qualitative assessment of the patient condition using fuzzy inductive reasoning [47,48]. A self-adaptive fuzzy controller with reinforcement learning is yet another technique applied to simulation of a paraplegic standing up [14]. Even for patient monitoring, adaptive controllers are being utilised for intelligent monitoring of diabetic patients [8]. A new type of adaptive fuzzy control system based on the Takagi-Sugeno Kang (TSK) modelling approach has also been shown to track accurately complex trajectories when controlling arm movements via electrical stimulation of muscles [43]. This approach has proved popular since it allows the integration of the popular Recursive Least-Squares parameter estimation for the various fuzzy partitions; the estimated model can either be linear or nonlinear.

### *3.6. Hybrid systems (neural, genetic and wavelets)*

Reasoning with fuzzy logic is possible without the need for much data because the backbone of the logic is expressed as IF–THEN rules. However, the rules cannot be expressed unless the logic is defined, when there are unknown logical relationships. Thus attempts are being made to combine different techniques such as neural networks and genetic algorithms, with fuzzy logic organising the mapping relationship by learning. Neurofuzzy networks were developed by fusing the ideas that originated in the fields of neural and fuzzy systems [10]. A neurofuzzy network attempts to combine the transparent, linguistic, symbolic representation associated with fuzzy logic with the architecture and learning rules commonly used in neural networks. These hybrid structures have both a qualitative and a quantitative interpretation and can overcome some of the difficulties associated with solely neural algorithms which can usually be regarded as black box mappings, and with fuzzy systems where few modelling and learning theories exist. Many applications are being reported using fuzzy-neural control [37] and modelling [35].

Although writing fuzzy rules is easy, specific forms of membership functions are much harder to derive. In this case a genetic algorithm (GA) is used to adjust the membership function towards convergence. GA's are exploratory search and optimisation methods that were devised on the principles of natural evolution and population genetics. Modelling clinical data can be achieved using genetic-fuzzy logic techniques [35].

Cascading two techniques is another approach to hybrid fuzzy control, for example, by using the discrete wavelet transform analysis to extract features from the clinical data, then feeding the features to a fuzzy logic system (clustering or neurofuzzy) to extract the final output [33]. This methodology was also applied for forecasting generalised epileptic seizures from the EEG signal by wavelet analysis and dynamic unsupervised fuzzy clustering [20]. The integration of evolutionary computing (genetic algorithms) to automatically optimise the parameters of fuzzy type controllers has also been considered: in the case of a self-organising fuzzy logic control (SOFLC) scheme for muscle relaxation [39] or a simple fuzzy logic based controller for functional electrical stimulation (FES) of hips [15].

### 3.7. Hierarchical and supervisory systems

A totally fuzzy logic-based hierarchical architecture for manipulating procedures on a complex process (i.e. the patient) has been developed [56]. The novel hierarchical architecture for fuzzy logic monitoring and control of intravenous anaesthesia has two main objectives: the primary task is to utilise auditory evoked response signals for augmenting cardiovascular and body function signs into a multi-sensor fuzzy model-based strategy for anaesthesia monitoring and control. The secondary task is to extend an existing fuzzy patient model for use as a training simulator.

As for supervisory control, a multiple drug haemodynamic control system by means of a fuzzy rule-based adaptive control system has been developed for controlling the mean arterial pressure and the cardiac output. Supervisory capabilities are added to ensure adequate drug delivery [23,24].

## 4. Fuzzy techniques for biomedical data analysis

### 4.1. Fuzzy clustering

Clustering algorithms are mainly concerned with partitioning the data into a number of subsets. Within each subset, the elements are similar to each other. On the other hand, elements from different sets are as different as possible. There are different fuzzy clustering techniques based on unsupervised learning such as relation criterion functions, object criterion functions, C-means clustering, etc. Most of the clustering techniques are being applied to diagnosis. Fuzzy C-means clustering was applied for brain injury using magnetic resonance images [63], and tumour measurement in response to treatment [65,67]. Fuzzy clustering has also been used for extracting single-unit spike trains from extracellular recordings containing the activity of several active cells [75]. The method has been shown to be more advantageous over other conventional approaches over a wide range of signal-to-noise ratios.

### 4.2. *Fuzzy classification*

Classification differs from clustering by the labelling method, the former giving a label to each data, while in the latter method a label is given to each data set. Supervised learning is usually used for classification. Although most of the fuzzy classification applications occur in the psychology field [41], there are also forensic applications [62], classification of pathophysiology laboratory data [59], and data screening for breast cancer [40].

### 4.3. *Fuzzy modelling and identification*

Fuzzy logic models can be developed from expert knowledge or from process (patient) input–output data. In the first case, fuzzy models can be extracted from the expert knowledge of the process. The expert knowledge can be expressed in terms of linguistics, which is sometimes faulty and requires the model to be tuned. Therefore, identifying the process is a more attractive way of using the help of an expert knowledge. This process requires defining the model input variables and the determination of the fuzzy model type. There are two ways to develop a fuzzy model, the first beings based on defining the initial parameters of the model (membership functions) and selecting the rules construction method (IF–THEN). Neurofuzzy algorithms are often used for the tuning of parameters [6,9]. The second method is used if there is no knowledge about the process, and/or when the rules and membership functions can be extracted directly from the data by clustering the input/output space [36,67].

## 5. Conclusions

The information gathered in this study has been arranged according to its time of publication with respect to the medical sectors as shown in Table 1. This will substantiate the actual state-of-the-art, and also the dynamic process of the information in each sector that can be determined. Table 2 considers the type of fuzzy technology used in medicine and healthcare arranged according to its time of publication. This shows the type of fuzzy technology developments in the field of medicine during the last decade. Merging Tables 1 and 2 will give an overview of the type of fuzzy technology applied in each medical field.

Based on this study, future developments of fuzzy control and monitoring technologies in medicine and healthcare can be forecast. The sectors of medical activities can be brought together in a hierarchical scheme according to the mode of the medical procedure. This means that significant methodologies, relationships and demands are correlated. This scheme substantiates the hypothesis that a successful application in one sector should lead to a successful application in neighbouring sectors.

Table 1
Number of fuzzy technology publications applied in each medical sectors based on time scale

| Publication year | <1989 | 1990 | 1991 | 1992 | 1993 | 1994 | 1995 | 1996 | 1997 | 1998 | 1999–2000 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| *Conservative disciplines* | | | | | | | | | | | |
| Internal medicine | – | – | – | – | 1 | – | – | – | 1 | – | – |
| Cardiology | – | – | – | – | – | 2 | 2 | – | 2 | 3 | 9 |
| Intensive care | 1 | – | – | – | – | 1 | – | – | – | 1 | 2 |
| Paediatry | – | – | – | – | – | – | – | – | – | – | 1 |
| Endocrinology | – | – | – | – | – | – | – | – | – | – | – |
| Oncology | – | – | – | – | – | 1 | 2 | – | 2 | 1 | 2 |
| Gerontology | – | – | – | – | 1 | – | – | 2 | 2 | 2 | 1 |
| General practice | 1 | 1 | – | – | 1 | 1 | 1 | 2 | 4 | 2 | – |
| *Invasive medicine* | | | | | | | | | | | |
| Surgery | – | – | – | – | 2 | 1 | – | 2 | 3 | 1 | 1 |
| Orthopaedics | – | – | – | – | | 1 | – | 1 | – | – | – |
| Anaesthesia | 4 | 1 | 1 | 4 | 4 | 4 | 2 | 5 | 7 | 2 | 7 |
| Artificial organs | – | – | – | – | – | – | 2 | 2 | 5 | 3 | 2 |
| *Regionally defined medical disciplines* | | | | | | | | | | | |
| Gynaecology | – | – | – | – | – | – | – | – | – | – | – |
| Dermatology | – | – | – | – | – | – | – | – | – | – | 2 |
| Dental medicine | – | – | – | – | – | 1 | – | – | – | – | – |
| Ophthalmology | – | – | – | – | – | – | – | – | – | – | – |
| Otology, rhinology etc | – | – | – | – | – | – | – | – | – | – | – |
| Urology | – | – | – | – | – | – | – | – | – | – | – |
| Neuromedicine– | | | | | | | | | | | |
| Neurology | – | – | – | – | – | – | – | – | – | – | 2 |
| Psychology | – | – | – | – | 1 | – | 1 | 2 | 1 | 2 | – |
| Psychiatry | – | – | – | – | – | – | 1 | | – | – | 1 |
| *Image and signal processing* | | | | | | | | | | | |
| Signal processing | 1 | – | – | – | – | 1 | 1 | 2 | 2 | 2 | 14 |
| Radiation medicine | – | – | – | – | – | – | – | – | – | – | – |
| Radiology | – | – | – | – | – | – | – | 1 | 1 | – | – |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Laboratory | | | | | | | | | | | |
| Biochemical & tests | 3 | 1 | – | – | 1 | 1 | – | – | – | – | 1 |
| Basic science | | | | | | | | | | | |
| Medical information | 2 | – | 2 | 1 | 2 | 4 | 1 | 1 | 1 | – | 6 |
| Anatomy, pathology, etc. | – | 1 | – | – | 2 | 1 | 2 | – | 1 | 2 | – |
| Physiology | 1 | – | – | – | – | – | – | – | 1 | – | 6 |
| Pharmacology | 1 | – | – | – | 1 | – | – | – | 1 | – | – |
| Education | 1 | – | – | – | 1 | 1 | – | – | 1 | 1 | 5 |
| Nursing | – | – | – | – | – | – | 1 | – | – | – | – |
| Healthcare | 1 | – | – | – | – | – | 2 | – | 1 | 1 | 10 |

Table 2
Type of fuzzy technology application in medicine and healthcare over time

| Publication year | <1989 | 1990 | 1991 | 1992 | 1993 | 1994 | 1995 | 1996 | 1997 | 1998 | 1999–2000 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Closed loop control | 4 | 1 | – | 1 | 3 | 5 | 3 | 6 | 9 | 3 | 13 |
| Open loop control | – | 1 | – | 1 | 1 | 3 | – | – | – | 2 | 1 |
| PI, PID | – | – | – | 1 | – | – | – | – | 1 | 1 | 2 |
| Identification | – | – | – | – | 1 | – | 1 | – | 1 | 1 | 4 |
| Model based | 3 | 1 | – | – | 3 | 1 | 5 | 4 | 8 | 6 | 13 |
| Adaptive | 2 | – | 1 | – | – | 2 | 4 | – | – | 1 | 12 |
| Monitoring | – | – | – | – | – | – | 3 | 2 | 1 | – | 3 |
| Classification | 1 | 1 | – | – | 1 | 3 | 1 | 3 | 8 | – | 11 |
| Self-Learning | – | – | – | – | – | – | – | – | 1 | 2 | 5 |
| Hybrid | – | – | – | 2 | – | 2 | 3 | 1 | 4 | 3 | 5 |

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## References

[1] Abbod MF, Linkens DA. Anaesthesia monitoring and control using fuzzy logic fusion. Journal of Biomedical Engineering — Applications, Basis & Communications, Special Issues on Control Methods in Anaesthesia 1994;10(4) 225–235.
[2] Akhavan S, Calva G. Automatic anomaly detection in ECG signal by fuzzy decision making. In: Proceedings of the 6th International Conference on Fuzzy Theory and Technology, vol. 1. 1998. p. 96–8.
[3] Al-Holou N, Joo DS. Development of a fuzzy logic based system to monitor the electrical responses of nerve fibre. Biomed Sci Instrum 1997;33:376–81.
[4] Allum JH, Honegger F, Troescher M. Principles underlying real-time nystagmus analysis of horizontal and vertical eye movements recorded with electro-, infra-red-, or video-oculographic techniques. J Vestib Res 1998;8(6):449–63.
[5] Asbury AJ, Brown BH, Linkens DA. Control of neuromuscular blockade by external feedback mechanism. Br J Anaesth 1980;52:633–4.
[6] Ashford JW, Shan M, Butler S, Rajasekar A, Schmitt FA. Temporal quantification of Alzheimer's disease severity: time index model. Dementia 1995;6(5):269–80.
[7] Astanin SV. A complex approach to modelling the functional status of a human operator based on the theory of fuzzy sets. Kosm Biol Aviakosm Med 1989;23(4):29–33.
[8] Bellazzi R, Siviero C, Stefanelli M, De Nicolao G. Adaptive controllers for intelligent monitoring. Art Intell Med 1995;7(6):515–40.
[9] Bleckert G, Oppel UG, Salzsieder E. Mixed graphical models for simultaneous model identification and control applied to the glucose-insulin metabolism. Comput Methods Programs Biomed 1998;56(2):141–55.
[10] Brown M, Harris CJ. A perspective and critique of adaptive neurofuzzy systems used for modelling and control applications. Int J Neural Syst 1995;6(2):197–220.
[11] Butt A, Acharya R, Sibata C, Shin KH. Surface matching of multimodality image volumes by a fuzzy elastic registration technique. Comput Med Imaging Graph 1998;22(1):13–23.
[12] Chen GH. Use of fuzzy mathematics to evaluate the teaching of students in the clinical setting. Chung Hua Hu Li Tsa Chih 1996;31(11):658–60.
[13] Chiodo F, Menditto A, Ouane-Keita F, Caroli S. The management of information: storage and retrieval of data. Ann Ist Super Sanita 1994;30(4):433–7.
[14] Davoodi R, Andrews BJ. Computer simulation of FES standing up in paraplegia: a self-adaptive fuzzy controller with reinforcement learning. IEEE Trans Rehabil Eng 1998;6(2):151–61.
[15] Davoodi R, Andrews BJ. Optimal control of FES-assisted standing up in paraplegia using genetic algorithms. Med Eng Phys 1999;21(9):609–17.
[16] Derrick JL, Thompson CL, Short TG. The application of a modified proportional-derivative control algorithm to arterial pressure alarms in anesthesiology. J Clin Monit Comput 1998;14(1):41–7.
[17] Garibaldi JM, Ifeachor EC. The development of a fuzzy expert system for the analysis of umbical cord blood. In: Szczepaniak PS, Lisboa PJG, Kacprzyk J, editors. Chapter in fuzzy systems in medicine. Berlin: Springer, Physica-Verlag, 2000. p. 652–68.
[18] Gath I, Bar-On E, Rogowski Z, Bental E. Automatic scoring of polygraphic sleep recordings: midazolam in insomniacs. Br J Clin Pharmacol 1983;16(l):89S–96S.
[19] Genaidy AM, Karwowski W, Christensen DM, Vogiatzis C, Deraiseh N, Prins A. What is heavy? Ergonomics 1998;41(4):420–32.
[20] Geva AB, Kerem DH. Forecasting generalised epileptic seizures from the EEG signal by wavelet analysis and dynamic unsupervised fuzzy clustering. IEEE Trans Biomed Eng 1998;45(10):1205–16.

[21] van Ginneken AM, Smeulders AW. Reasoning in uncertainties. An analysis of five strategies and their suitability in pathology. Anal Quant Cytol Histol 1991;13(2):93–109.
[22] Greenhow SG, Linkens DA, Asbury AJ. Development of an expert system advisor for anaesthetic control. Comput Methods Programs Biomed 1992;37(3):215–29.
[23] Held CM, Roy RJ. Multiple drug hemodynamic control by means of a supervisory-fuzzy rule-based adaptive control system: validation on a model. IEEE Trans Biomed Eng 1995;42(4):371–85.
[24] Held CM, Roy RJ. Hemodynamic management of congestive heart failure by means of a multiple model rule-based control system using fuzzy logic. IEEE Trans Biomed Eng 2000;47(1):115–423.
[25] Jensen ON, Mortensen P, Vorm O, Mann M. Automation of matrix-assisted laser desorption/ionisation mass spectrometry using fuzzy logic feedback control. Anal Chem 1997;69(9):1706–14.
[26] Jin S, Ye K, Shimizu K. Efficient fuzzy control strategies for the application of pH-state to fed-batch cultivation of genetically engineered *Escherichia coli*. J Chem Technol Biotechnol 1994;61(3):273–81.
[27] Kachukhashvili GS, Tsiskarishvili NE, Dubovik MV, Badiashvili GV. The use of fuzzy sets techniques in managing health organisations. Medinfo 1995;8 Pt 1:541.
[28] Kaufmann R, Becker K, Nix C, Reul H, Rau G. Fuzzy control concept for a total artificial heart. Artif Organs 1995;19(4):355–61.
[29] Kokutei K, Yamashita H, Horie K, Funatsu H. Diabetic retinopathy score and fuzzy logic in therapy. Nippon Ganka Gakkai Zasshi 1993;97(5):632–8.
[30] Kovacs M, Juranovics J. Auctoritas psychiatric expert system shell, Medinfo 1995;8 Pt 2:997.
[31] Krell G, Tizhoosh HR, Lilienblum T, Moore CJ, Michaelis B. Enhancement and associative restoration of electronic portal images in radiotherapy. Int J Med Inf 1998;49(2):157–71.
[32] Linkens DA, Hasnain SB. Self-organising fuzzy logic control and its application to muscle relaxation anaesthesia. IEE Proc PtD. Control theory and applications, vol. 138. 1991. p. 274–84.
[33] Linkens DA, Abbod MF, Backory JK. Closed-loop control of anaesthesia using a Wavelet-based fuzzy logic system, EUFIT'97, 8–12 September, Aachen, Germany, 1997.
[34] Linkens DA, Mahfouf M. Fuzzy logic knowledge based control of muscle relaxation. In: IFAC Proceedings on Modelling and Control of Systems, Venice, Italy, 1988. p. 185–90.
[35] Linkens DA, Abbod MF. Medical applications of fuzzy logic control. International School on Fuzzy Logic Control, Delft University of Technology, 20–24 April, commissioned paper.
[36] Linkens DA, Abbod MF, Backory JK, Shieh JS. Closed-loop control of anaesthesia using fuzzy logic. In: Lisboa PJG, Tsumoto S, Szczepaniak PS, editors. Fuzzy systems in medicine. Berlin: Springer, series Studies in Fuzziness and Soft Computing. Kacprzyk J, editor. p. 467–83.
[37] Lee M, Ahn JM, Min BG, Lee SY, Park CH. Total artificial heart using neural and fuzzy controller. Artif Organs 1996;20(11):1220–6.
[38] Mahfouf M, Abbod MF. Self-adaptive and self-organising control applied to nonlinear multivariable anaesthesia: a comparative model-based study. In: Linkens, DA, editor. Intelligent control in biomedicine. London: Taylor & Francis, 1994. [Chapter 4], p. 79–132.
[39] Mahfouf M, Linkens DA, Abbod MF. Multi-objective genetic optimisation of GPC and SOFLC tuning factors — a fuzzy-based ranking method. In: Proceedings of the IEE. Pt. D — control theory and practice 2000;147(3):344–54.
[40] Mallinson H, Bentley P. Evolving fuzzy rules for pattern recognition. Computational intelligence for modelling, control and automation. Evolutionary computation and fuzzy logic for intelligent control, knowledge acquisition and information retrieval, vol. 55. Amsterdam: IOS Press, 1999. p. 184–91.
[41] Massaro DW, Cohen MM. Perceiving speech from inverted faces. Percept Psychophys 1996;58(7):1047–65.
[42] McCall JAW, Petrovski A. A decision support system for cancer chemotherapy using genetic algorithms. Computational intelligence for modelling, control and automation. Evolutionary computation and fuzzy logic for intelligent control, knowledge acquisition and information retrieval, vol. 55. Amsterdam: IOS Press, 1999. p. 65–70.
[43] Micera S, Sabatini AM, Dario P. Adaptive fuzzy control of electrically stimulated muscles for arm movements. Med Biol Eng Comput 1999;37(6):680–5.
[44] Moriguchi I, Hirano H, Hirono S. Prediction of the rodent carcinogenicity of organic compounds from their chemical structures using the FALS method. Environ Health Perspect 1996;104(5):1051–8.

[45] Mussivand T. Future prospects for cardiac assisted patients. Int J Artif Organs 1998;21(3):129–30.
[46] Naranjo CA, Bremner KE, Bazoon M, Turksen IB. Using fuzzy logic to predict response to citalopram in alcohol dependence. Clin Pharmacol Ther 1997;62(2):209–24.
[47] Nebot A, Cellier FE, Linkens DA. Synthesis of an anaesthetic agent administration system using fuzzy inductive reasoning. Artif Intell Med 1996;8(2):147–66.
[48] Nebot A, Cellier FE, Vallverdu M. Mixed quantitative/qualitative modelling and simulation of the cardiovascular system. Comput Methods Programs Biomed 1998;55(2):127–55.
[49] Ogawa S, Itoh K, Omoto K, Cheng X, Ohya A, Akiyama I. 1998, Three-dimensional ultrasonic imaging for diagnosis of breast tumor. In: Proceedings of the IEEE Ultrasonics Symposium, vol. 2. 1998. p. 1677–82.
[50] Orimo A, Wakabayashi M, Sasada S. Analysis of the variations of clinical test data on fasting therapy using fuzzy similarity dendrogram. Rinsho Byori 1993;41(12):1365–72.
[51] Oshita S, Nakakimura K, Kaieda R, Murakawa T, Tamura H, Hiraoka I. Application of the concept of fuzzy logistic controller for treatment of hypertension during anaesthesia. Masui 1993;42(2):185–9.
[52] Sadegh-Zadeh K. Fundamentals of clinical methodology: nosology. Artif Intell Med 1999;17:87–108.
[53] Sadegh-Zadeh K. Fuzzy health, illness, and disease. J. Med. Philos. 2000; 25(5): 605–638.
[54] Sadegh-Zadeh K. Fuzzy genomes. Artif. Intell. Med. 2000b;18:1–28.
[55] Sheppard LC, Shotts JF, Roberson NF, Wallace FD, Kouchoukos NT. Simultaneous modelling of pharmacokinetics and pharmacodynamics: application to d-tubocurarine. Clin Pharmacol Therapeutics 1979;25:358.
[56] Shieh JS, Abbod MF, Linkens DA, Peacock JE, 1999. Hierarchical fuzzy-based support system for anaesthesia monitoring and control. In: Proceedings of the IEE-PtD. Control theory and applications, 146(3);265–72.
[57] Stadelmann A, Abbas S, Zahlmann G, Bruns W, Hennig I. DIABETEX decision module 2-calculation of insulin dose proposals and situation recognition by means of classifiers. Comput Methods Programs Biomed 1990;32(3/4):333–7.
[58] Schaublin J, Derighetti M, Feigenwinter P, Petersen-Felix S, Zbinden AM. Fuzzy logic control of mechanical ventilation during anaesthesia. Br J Anaesth 1996;77(5):636–41.
[59] Shimizu H, Haida M, Niwa M. Interpretation of pathophysiology by laboratory data (3). A consultation program based on clinical laboratory data. Tokai J Exp Clin Med 1990;15(1):51–79.
[60] Steimann F. The interpretation of time-varying data with DIAMON-1. Artif Intell Med 1996;8(4):343–57.
[61] Sun Y, Kohane I, Stark AR. Fuzzy logic assisted control of inspired oxygen in ventilated new-born infants. In: Proceedings of the Annual Symposium on Computational Application Medical Care. 1994. p. 756–61.
[62] Takeuchi T. Application of fuzzy inference to personal identification/sex determination from teeth. Nippon Hoigaku Zasshi 1993;47(3):239–49.
[63] Thatcher RW, Camacho M, Salazar A, Linden C, Biver C, Clarke L. Quantitative MRI of the gray-white matter distribution in traumatic brain injury. J Neurotrauma 1997;14(1):1–14.
[64] Toglia MP, Neuschatz JS, Goodwin KA. Recall accuracy and illusory memories: when more is less. Memory 1999;7(2):233–56.
[65] Vaidyanathan M, Clarke LP, Hall LO, Heidtman C, Velthuizen R, Gosche K, Phuphanich S, Wagner H, Greenberg H, Silbiger ML. Monitoring brain tumour response to therapy using MRI segmentation. Magn Reson Imaging 1997;15(3):323–34.
[66] Vasileva OI, Ionov IP, Kantor PS, U'lianov SV. Dual control of artificial ventilation processes of the lungs using a fuzzy regulator in the feedback circuit. Med Tekh 1989;1:11–21.
[67] Velthuizen RP, Clarke LP, Phuphanich S, Hall LO, Bensaid AM, Arrington JA, Greenberg HM, Silbiger ML. Unsupervised measurement of brain tumour volume on MR images. J Magn Reson Imaging 1995;5(5):594–605.
[68] Wang RH, Sun ZQ. Evaluation of self-taught ability of nursing administrators with fuzzy medicine. Chung Hua Hu Li Tsa Chih 1996;31(7):395–6.
[69] Westenskow DR. Fundamentals of feedback control: PID, fuzzy logic, and neural networks. J Clin Anesth 1997;9(Suppl. 6):33S–5S.
[70] Wolf M, Keel M, von Siebenthal K, Bucher HU, Geering K, Lehareinger Y, Niederer P. Improved monitoring of pre-term infants by Fuzzy Logic. Technol Health Care 1996;4(2):193–201.

[71] Yamaguchi K, Kiryu T, Tanaka K, Saitoh Y. Remote workload control system of cycle ergometer for older adults. Trans Inst Elec Informations Commun Eng 2000;83(2):840–7.
[72] Ying H, Sheppard LC. Regulating mean arterial pressure in post-surgical cardiac patients. A fuzzy logic system to control administration of sodium nitroprusside. IEEE Eng Med Biol-Mag 1994;13(5):671–7.
[73] Zadeh LA. Fuzzy sets. Information and Control 1965;3:338–53.
[74] Zbinden AM, Feigenwinter P, Petersen-Felix S, Hacisalihzade S. Arterial pressure control with isoflurane using fuzzy logic. Br J Anaesth 1995;74(1):66–72.
[75] Zouridakis G, Tam DC. Identification of reliable spike templates in multi-unit extracellular recordings using fuzzy clustering. Comput Methods Programs Biomed 2000;61(2):91–8.