# Fuzzy Systems in Medicine

**Klaus-Peter Adlassnig**
Department of Medical Computer Sciences
Section on Medical Expert and Knowledge-Based Systems
University of Vienna Medical School
Spitalgasse 23, A-1090 Vienna, Austria
e-mail: kpa@akh-wien.ac.at

## Abstract

In the near future, every medical information system will be equipped with a function that provides knowledge-based decision support. Data-driven knowledge-based decision support consists, in the first place, of a medical data-to-concept conversion step and, second, a knowledge base containing medical relationships from medical concepts to decisions. Both, concept and relationship modeling in medicine can be done by using fuzzy sets, fuzzy relationships, and fuzzy decision making algorithms to conserve the inherent fuzziness of medical concepts and medical relationships. Examples of the application of type-n fuzzy sets to model medical concepts and of fuzzy logic, fuzzy decision graphs, fuzzy control, and fuzzy automata in medical diagnosis, interpretative analysis of test results, device control, and data monitoring are given in the present study.

**Keywords:** Knowledge-Based Methodology, Fuzzy Concepts, Fuzzy Relationships, MedFrame/CADIAG-IV, FuzzyTempToxopert, FuzzyKBWean, FuzzyARDS.

## 1 Introduction

Patient-specific diagnostic and therapeutic decision support will become a part of every medical information system in the near future [1].

Hospital information systems are being equipped with rule firing mechanisms to automatically generate intelligent alerts, warnings, and recommendations to the attending physician [2–4]. A rule editor with access to medical data dictionaries allows the user to define rules on contraindication alerts, drug interaction warnings, diagnostic and treatment recommendations, etc.

Some laboratory information systems generate the written laboratory report automatically by means of an intelligent reporting system based on medical knowledge stored in a knowledge base [5,6]. These systems may soon become available on Web servers, thus providing worldwide service for medical laboratories [7,8].

Patient data management systems (PDMSs) in intensive care units (ICUs) try to overcome the flood of information by combining and aggregating individual information items to high-level descriptions of patients' findings [9,10]. These high-level descriptions usually constitute the medical terms used by physicians in communication regarding the patient.

Last but not least, stand-alone as well as integrated, frequently very extensive medical consultation systems, are already able to support the differential diagnostic process in areas such as internal medicine: support that is far-reaching and frequently outperforms the diagnostic ability of the individual physician. This becomes obvious in rare medical cases or in cases of multimorbidity [11–14].

## 2 Knowledge-Based Systems in Medicine

Medicine naturally applies linguistic concepts to model medical knowledge such as disease descriptions, treatment recommendations, prognostic information, and best medical practice management guidelines. Therefore, statements like "Highly increased amylase activity nearly confirms acute pancreatitis" may be found as part of diagnostic knowledge.

Directly observed and measured patient data from patient history, physical examination, laboratory tests, and clinical investigations are usually interpreted and associated with meaning. For instance, an α-amylase value 10 times the upper reference value (where the reference values depend on the specific analysis in the respective laboratory) is considered highly increased.

A data-to-concept conversion step links the observational and measurement level with the concept and knowledge level. Any data-driven knowledge-based system includes such a conversion step. Non-interpreted observed or measured (syntactic) data are transformed into interpreted, meaningful (semantic) information concerning the patient. This functionality is the first step to intelligence in knowledge-based systems in medicine.

## 3 Fuzzy Systems in Medicine

Due to the inherent fuzziness of linguistic concepts in medicine, first, the data-to-concept conversion step and, second, any modelling of knowledge in medicine can employ fuzzy set theory and its derived theories to model interpreted medical entities such as recounted patient history items, perceived physical signs, interpreted laboratory measurements, pathophysiological states, diagnostic, therapeutic, and prognostic concepts as type-n fuzzy sets. Any n-ary relationship between these fuzzy concepts that is used to model medical knowledge may itself be fuzzy.

Moreover, algorithms devised to arrive at conclusions such as alerts, warnings, recommendations, diagnoses, therapies, prognoses, and patient management decisions from instantiated fuzzy concepts—that are the result of the data-to-concept conversion step—should consider the fuzziness of concepts and the relationships between them. They should be able to propagate and conserve fuzziness. Algorithms with these properties stem from fuzzy logic, fuzzy graph theory, fuzzy control, fuzzy automata theory, and others.

### 3.1 MedFrame/CADIAG-IV: An Internet-Based Framework for Diagnostic and Therapeutic Decision Support

MedFrame is intended to form a broad platform for the development of various knowledge-based systems in medicine, e.g., to host knowledge bases for differential diagnosis or differential therapy in the entire field of internal medicine or for smaller subspecialties of medicine. It can also host knowledge-based systems for interpretive analysis of laboratory test results. An integrated patient data and medical knowledge base, knowledge base editor modules, differential diagnosis and therapy modules, and an immediate case evaluation module will constitute the core of MedFrame.

MedFrame/CADIAG-IV will be upward compatible with respect to the available medical knowledge bases contained in former CADIAG systems [15]. Improved data-to-concept conversion with extended context dependency, stepwise abstraction of high-level medical concepts including temporal concepts, extended frame and rule-based knowledge representation, inference procedures able to infer positive and negative diagnostic hypotheses as well as positive and negative therapy proposals, are features of MedFrame/CADIAG-IV [16–20].

### 3.2 FuzzyTempToxopert: A Fuzzy System in the Toxoplasmosis Laboratory

FuzzyTempToxopert interprets toxoplasmosis serology test results obtained in the course of screening for *Toxoplasma gondii* infections in pregnant women. The antibody tests are performed at the toxoplasmosis laboratory of the Department of Pediatrics and Adolescent Medicine in the Vienna General Hospital. FuzzyTempToxopert interprets them in the course of time and automatically provides a diagnostic interpretation and, most importantly, therapeutic recommendations to avoid fetal damage or subsequent harm to the child.

FuzzyTempToxopert contains a knowledge base in the form of a decision graph. Decision rules control the transition from one decision node to the next; each transition step is activated by obtaining a further serological test result. In order to arrive at correct diagnostic interpretations, a minimal temporal distance from one test to the next has to be maintained. These minimal distances are checked by applying fuzzy sets modeling temporal concepts such as 'at least three weeks' [6,7].

### 3.3 FuzzyKBWean: Knowledge-Based Weaning from Artificial Ventilation

FuzzyKBWean is an open-loop fuzzy control system for optimization and quality control of the

ventilation and weaning process in patients after cardiac surgery at one of the ICUs of the Vienna General Hospital, the main teaching hospital of the University of Vienna Medical School.

The system is directly connected to the PDMS of the ICU and is run on bedside computers.

According to the well-known structure of fuzzy control systems, a fuzzification step is followed by a fuzzy rule evaluation. The fuzzy rules in FuzzyKBWean contain linguistically expressed physiological parameters of the patient and actual ventilator settings in their antecedents, yet crisp proposals for new settings of the ventilator as a consequences of the rules. Thus, it is possible to apply the Sugeno control method to combine rule output of the same kind [21].

A recent clinical trial showed that a number of appropriate proposals for ventilator settings are given at stages of the weaning process, earlier than the attending personal would react. Thus the proposed adjustments to stabilize the ventilated patient, to start and end the weaning process, and finally to extubate the patient, caused less suffering for the patient and reduced costs.

### 3.4 FuzzyARDS: Knowledge-Based Patient Monitoring

FuzzyARDS is an intelligent online program for monitoring the intensive care data of patients with acute respiratory distress syndrome (ARDS) [10]. Its clinical aim is to detect ARDS in patients as early as possible and to provide appropriate therapeutic advice.

ARDS is an ill-defined medical entity and is modeled using the concept of fuzzy automata. States in these automata are considered to be a patient's pathophysiological state or entry criteria for different forms of ARDS therapy. Patients may be partially assigned to one or several states in such an automaton at the same point in time. Transitions in the automata carry fuzzy conditions that have to be true or partially true to transit from one state to another. Fuzzy conditions are usually high-level medical concepts such as 'low', 'normal', or 'high $F_iO_2$', 'hypoxemia', or linguistically expressed trend information, e.g., 'rapidly improving oxygenation'. These high-level concepts are permanently evaluated

in a data-to-concept conversion step according to adjustable time granularity [22,23].

## 4 Conclusion

Fuzzy set theory and its derived theories provide a highly suitable and broadly applicable basis for developing knowledge-based systems in medicine [24–32]. Clinical studies conducted so far have demonstrated the appropriateness of the respective patient data and fuzzy knowledge representation and the selected fuzzy inference mechanisms with respect to the required medical applicability and the achieved correctness of results. They further revealed the immediate intuitive understanding of basic ideas of fuzzy set theory and fuzzy logic on the part of medical users.

## References

[1] R.B. Altman (1999). AI in Medicine—The Spectrum of Challenges from Managed Care to Molecular Medicine. AI Magazine, Fall 1999, 67–77.

[2] S.A. Abookire et al. (2000). Improving Allergy Alerting in a Computerized Physician Order Entry System. In J.M. Overhage, editor, *Proceedings of AMIA 2000*, Hanley & Belfus, Inc. Philadelphia, 2–6.

[3] M.M. Shabot, M. LoBue, J. Chen (2000). Wireless Clinical Alerts for Physiologic, Laboratory and Medication Data. In J.M. Overhage, editor, *Proceedings of AMIA 2000*, Hanley & Belfus, Inc. Philadelphia, 789–793.

[4] Cerner Corporation (1996). Discern Dialogue, Discern Insights—Exexutable Knowledge for Clinical Decision Support. Cerner Corporation, 2800 Rockcreek Parkway, Kansas City, USA.

[5] K.-P. Adlassnig, W. Horak (1995). Development and Retrospective Evaluation of HEPAXPERT-I: A Routinely-Used Expert System for Interpretive Analysis of Hepatitis A and B Serologic Findings. *Artificial Intelligence in Medicine* 7, 1–24.

[6] S. Nagy (1996). *Time Dependent Clinical Decision Support Systems for Laboratory Routine Work—Applications for the Screening of Infection with Toxoplasma Gondii*, Dissertation, Vienna, Technical University of Vienna.

[7] D. Kopecky, M. Hayde, K.-P. Adlassnig, A.-R. Prusa, B. Panzenböck (2000). Knowledge-Based Interpretation of Toxoplasmosis Serology Test Results Including Fuzzy Temporal Concepts—The ToxoNet System. In K.-P. Adlassnig, editor, *Fuzzy Diagnostic and Therapeutic Decision Support*, Wien, Österreichische Computer Gesellschaft, 171–179.

[8] C. Chizzali-Bonfadin, K.-P. Adlassnig, M. Kreihsl, A. Hatvan, W. Horak (1997). A WWW-Accessible Knowledge Base for the Interpretation of Hepatitis Serologic Tests. *International Journal of Medical Informatics* 47, 57–60.

[9] F. Steimann, K.-P. Adlassnig (1994). Clinical Monitoring with Fuzzy Automata. *Fuzzy Sets and Systems* 61, 37–42.

[10] H. Steltzer, B. Trummer, W. Höltermann, G. Kolousek, P. Fridrich, K. Lewandowski, K.-P. Adlassnig, A.F. Hammerle (1999). Wissensbasierte Diagnostik und Therapieempfehlung mit Methoden der Fuzzy-Set-Theorie bei Patienten mit akutem Lungenversagen (ARDS). *Anästhesiologie Intensivmedizin Notfallmedizin Schmerztherapie* 34, 218–223.

[11] G.O. Barnett, J.J. Cimino, J.A. Hupp, E.P. Hoffer (1987). DXplain—An Evolving Diagnostic Decision-Support System. *JAMA* 258, 67–74.

[12] R.A. Bankowitz et al. (1989). A Computer-Assisted Medical Diagnostic Consultation Service. *Annals of Internal Medicine* 110, 824–832.

[13] L.M. Lau, H.R. Warner (1992). Performance of a Diagnostic System (Iliad) as a Tool for Quality Assurance. *Computers and Biomedical Research* 25, 314–323.

[14] H. Leitich, P. Kiener, G. Kolarz, C. Schuh, W. Graninger, K.-P. Adlassnig (2001). A Prospective Evaluation of the Medical Consultation System CADIAG-II/RHEUMA in a Rheumatological Outpatient Clinic. *Methods of Information in Medicine* 40, 213–220.

[15] K.-P. Adlassnig, G. Kolarz, W. Scheithauer, H. Grabner (1986). Approach to a Hospital-Based Application of a Medical Expert System. *Medical Informatics* 11, 205–223.

[16] G. Kolousek (1997). *The System Architecture of an Integrated Medical Consultation System and Its Implementation Based on Fuzzy Technology.* Dissertation, Vienna, Technical University of Vienna.

[17] K. Boegl (1997). *Design and Implementation of a Web-Based Knowledge Acquisition Toolkit for Medical Expert Consultation Systems.* Dissertation, Vienna, Technical University of Vienna.

[18] T.E. Rothenfluh, K. Bögl, K.-P. Adlassnig, (2000). Representation and Acquisition of Knowledge for a Fuzzy Medical Consultation System. In P.S. Szczepaniak, P.J. Lisboa, S. Tsumoto, editors, *Fuzzy Systems in Medicine*, Heidelberg, Springer, 636–651.

[19] K. Boegl, H. Leitich, G. Kolousek, T. Rothenfluh, K.-P. Adlassnig (1996). Clinical Data Interpretation in MedFrame/CADIAG-4 Using Fuzzy Sets. *Biomedical Engineering—Applications, Basis & Communications* 8, 488–495.

[20] L. Brein, K.-P. Adlassnig, G. Kolousek (1998). Rule Base and Inference Process of the Medical Expert System CADIAG-IV. In R. Trappl, editor, *Cybernetics and Systems'98*, Vienna, Schottengasse 3, A-1010, Austrian Society for Cybernetic Studies, 155–159.

[21] Ch. Schuh (1998). *Wissensbasierte Entwöhnung vom Respirator unter Verwendung von Fuzzy- und Nichtfuzzy-Regelungsmodellen.* Dissertation, Vienna, Technical University of Vienna.

[22] F. Steimann, K.-P. Adlassnig (1994). Two-Stage Interpretation of ICU Data Based on Fuzzy Sets, In *AI in Medicine: Interpreting Clinical Data*, Stanford 1994 Spring Symposium Series, Stanford University, American Association for Artificial Intelligence, 152–156.

[23] F. Steimann, K.-P. Adlassnig (1994). Clinical Monitoring with Fuzzy Automata. *Fuzzy Sets and Systems* 61, 37–42.

[24] K.-P. Adlassnig (1982). A Survey on Medical Diagnosis and Fuzzy Subsets. In M.M. Gupta, E. Sanchez, editors, *Approximate Reasoning in Decision Analysis*, North-Holland Publishing Company, Amsterdam, 203–217.

[25] J.E. Maiers (1985). Fuzzy Set Theory and Medicine: The First Twenty Years and Beyond. In *Proceedings of Ninth Annual Symposium on Computer Applications in Medical Care*, New York, USA, IEEE, 325–329.

[26] F. Steimann (1997). Fuzzy Set Theory in Medicine. *Artificial Intelligence in Medicine* 11, 1–7.

[27] P.S. Szczepaniak, P.J.G. Lisboa, J. Kacprzyk, editors, (2000). *Fuzzy Systems in Medicine*, Physica-Verlag, Heidelberg.

[28] H.-N. Teodorescu, A. Kandel, L.C. Jain, editors, (1999). *Fuzzy and Neuro-Fuzzy Systems in Medicine*, CRC Press LLC, Boca Raton, Florida.

[29] J.N. Mordeson, D.S. Malik, S.-C. Cheng, (2000). *Fuzzy Mathematics in Medicine*, Physica-Verlag, Heidelberg.

[30] F. Steimann, guest editor, (2001). Fuzzy Theory in Medicine, *Artificial Intelligence in Medicine* 21.