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Fuzzy methods in clinical research and patient care

Klaus-Peter Adlassnig*

Section for Artificial Intelligence and Decision Support, Center for Medical Statistics, Informatics, and Intelligent Systems, Medical University of Vienna, Spitalgasse 23, A-1090 Vienna, Austria
And Medexter Healthcare GmbH, Borschkegasse 7/5, A-1090 Vienna, Austria

Abstract

Health IT
Health information technology (IT) systems gather, store, transfer, and display the medical data of patients in a computerized and structured form. Examples are patient history data, signs collected during the physical examination, laboratory test results, and findings from clinical investigations (imaging, endoscopy, histology, genetic, and others). These describe the present or previous states of a patient's health (or illness)[1].
In order to draw conclusions about patient care based on these data in a partly or fully automated manner, one needs what is generally known as medical knowledge. One also needs this medical knowledge in a computerized and structured form. How to interpret a patient's symptoms or laboratory data, how to administer medication but avoid adverse drug events, how to detect any worsening of the disease or identify chronic disease, and how to monitor and curb healthcare-associated infections at the medical institution—all of these are examples of smaller or larger cutouts of the large body of medical knowledge.
Clinical decision support
Combining digitized patient medical data with digitized medical knowledge to produce diagnostic, therapeutic, prognostic, or patient management suggestions is currently referred to as clinical decision support (CDS)[2]. In former times, such methods or systems were known as computer-assisted diagnosis and therapy, medical expert systems, or artificial intelligence in medicine.
To digitize medical knowledge formally, one needs to discern, formalize, and represent medical entities and their inter-relationships, which characterize the clinical topic under consideration. Medical entities include symptoms, signs, laboratory test results, clinical findings, diseases or diagnoses, therapies, and management tasks. Relationships between them may be of various types. We distinguish between definitional, causal, statistical, and heuristic bi- and multi-valued relationships, including procedures and algorithms.

* Corresponding author. Tel.: +43-1-40400-66680; fax: +43-1-40400-66250.
E-mail address: klaus-peter.adlassnig@meduniwien.ac.at

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Fuzzy sets

In general, medical entities such as fever, leukopenia, or hypoxemia are characterized by linguistic uncertainty[3,4]. The unsharpness of boundaries in these linguistic terms is modeled by fuzzy sets. Degrees of compatibility (degrees of membership) between raw—observed or measured—data and the linguistic terms under consideration are established.

Fuzzy logic

Many relationships between medical entities are characterized by propositional uncertainty, which is due to the incompleteness of medical conclusions. Such incompleteness may be due to a variety of causes: unknown territories in medicine, physiological diversity, and the sheer complexity of the human being—to name three. Propositional uncertainty is modeled by truth values between zero and one. One example is the medical proposition "Highly increased amylase activity is almost confirming acute pancreatitis", where the test result "highly increased amylase activity" and the diagnosis "acute pancreatitis" are connected by "almost confirming", which is substituted by the truth value ".95".

When concrete measurements map into fuzzy sets, the results are combined with truth values of medical propositions, and logical conclusions are drawn. One preferred method is the compositional rule of fuzzy inference, in several forms and successively. The results are fully or partly confirmed conclusions and/or refutations [5, 6].

The differential diagnostic consultation systems CADIAG-2 to CADIAG-4/MedFrame are examples of the successful application of fuzzy set theory and fuzzy logic in this manner [7, 8]. These systems were integrated into the medical information system of the Vienna General Hospital, Austria, and extensively tested in the clinical setting—in rheumatology, gastroenterology, and hepatology [9, 10].

Moni, a system for the surveillance of healthcare-associated infections, is based on the same formal principles. It monitors various forms of septicemia, pneumonia, urinary tract infection, and central-venous catheter-associated infection. It is routinely operated at 14 intensive care units, serving more than 140 beds at the Vienna General Hospital, Austria [11, 12].

Fuzzy automata

This methodology offers an interesting way to calculate "fuzzy states" of patients in a clear and clinically comprehensible manner. These states represent physiological or pathophysiological states—based on measured patient data—and allow for grades of "health" or "illness". States are characterized by linguistic terms and state transitions are described by linguistic instructions. Newly arriving measured data puts the automaton into new states—an interesting dynamic property which is highly welcomed by the medical community [13].

One example is FuzzyARDS, an automaton modelling the states of the adult respiratory distress (ARDS) syndrome and pointing to possible therapies [14]. The clinical models of ARDS vary from clinic to clinic and from place to place. Implementing them as different specific automata allows excellent comparison of the different ARDS care procedures.

Fuzzy control

If medical devices need to be controlled, but control rules are heuristic, then fuzzy control yields powerful solutions. It might be advisable to follow an open-loop control cycle, with a human physician carefully examining the control output and performing the actual control.

One example of this is FuzzyKBWean. It is an open-loop fuzzy control system for the optimization and quality control of the ventilation and weaning process in patients after cardiac surgery at one of the intensive care units of the Vienna General Hospital, Austria [15, 16].

Fuzzy Arden Syntax

Arden Syntax is a medical knowledge representation and processing language, issued and supported by Health Level Seven (HL7) International, a standard developing organization for health IT standards[17]. In 2013, the Health Level Seven Arden Syntax for Medical Logic Systems, version 2.9, including fuzzy methodologies, was issued by HL7 and approved by the American National Standards Institute[18,19]. A complete software implementation resulting in a broadly-applicable, scalable technology platform for extended CDS is now available[20].

Final remarks

In the future, any clinical activity will be either supported or substituted by knowledge-based decision software—at the hospital ward, the laboratory, the intensive care unit, the physician's practice, and as part of health and medical apps. Fuzzy theories will serve as a basis for many of these clinically applied systems.

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References

1. Evans RS. Electronic Health Records: Then, Now, and in the Future. *Yearbook of Medical Informatics* 2016; Suppl. **1:** 48–61.
2. Greenes RA. *Clinical Decision Support: The Road to Broad Adoption*. 2nd ed. Amsterdam: Academic Press; 2014
3. Adlassnig K-P Uniform Representation of Vagueness and Imprecision in Patient's Medical Findings Using Fuzzy Sets. In: Trappl R, editors. *Cybernetics and Systems'88*. Dordrecht: Kluwer Academic Publishers; 1988. p. 685–692.
4. Adlassnig K-P, Blacky A, Mandl H, Rappelsberger A, Koller W. (2014) Fuzziness in Healthcare-Associated Infection Monitoring and Surveillance. In: Winston A, Melek W, Hall P, McKenzie S, Gibbs M, Adamson G, editors. *Proceedings of the 2014 IEEE Conference on Norbert Wiener in the 21st Century – Driving Technology's Future*, Institute of Electrical and Electronics Engineers (IEEE), Piscataway, p. 1-7.
5. Adlassnig K-P. A fuzzy logical model of computer-assisted medical diagnosis. *Methods of information in medicine* 1980; **19**: 141–8.
6. Adlassnig K-P. Fuzzy set theory in medical diagnosis. *IEEE Transactions on Systems, Man, and Cybernetics* 1986; **16(2):** 260–5.
7. Adlassnig K-P, Kolarz G. CADIAG-2: Computer-assisted medical diagnosis using fuzzy subsets. In: Gupta MM, Sanchez E, editors. *Approximate reasoning in decision analysis*. Amsterdam: North-Holland Publishing Company; 1982. P. 219–247.
8. Brein L, Adlassnig K-P, Kolousek G. Rule base and inference process of the medical expert system CADIAG-IV. In: Trappl R, editor. *Cybernetics and Systems'98.* Vienna: Austrian Society for Cybernetic Studies; 1998. p. 155–9.
9. Leitich H, Kiener P, Kolarz G, Schuh C, Graninger W, Adlassnig K-P. A prospective evaluation of the medical consultation system CADIAG-II/RHEUMA in a rheumatological outpatient clinic. *Methods of Information in Medicine* 2001; **40:** 213–220.
10. Leitich H, Adlassnig K-P, Kolarz G. Evaluation of two different models of semiautomatic knowledge acquisition for the medical consultant system CADIAG-II/RHEUMA. *Artificial Intelligence in Medicine* 2002; **25:** 215–225.
11. De Bruin JS, Adlassnig K-P, Blacky A, Mandl H, Fehre K, Koller W. Effectiveness of an automated surveillance system for intensive care unit-acquired infections. *Journal of the American Medical Informatics Association* 2013; **20**(2): 369–372.
12. De Bruin JS, Adlassnig K-P, Blacky A, Koller W. Detecting borderline infection in an automated monitoring system for healthcare-associated infection using fuzzy logic. *Artificial Intelligence in Medicine* 2016; **69;** 33–41.
13. Steimann F, Adlassnig K-P. Clinical monitoring with fuzzy automata. *Fuzzy Sets and Systems* 1994; **61:** 37–42.
14. Trummer B, Steltzer H, Kolousek G, Adlassnig K.-P, Hammerle AF. Knowledge-based definition of ards therapy entry criteria using fuzzy set theory. *Acta Anaesthesiologica Scandinavica* 1998; **42:** 238–9.
15. Hiesmayr M, Gamper J, Neugebauer T, Mares P, Adlassnig K.-P, Haider W. Clinical application of patient data management systems (PDMS): Computer-assisted weaning from artificial ventilation (KBWEAN). In: Lenz K, Metnitz PGH, editors. *Patient data management in intensive care.* Wien: Springer-Verlag; 1993. p. 129–138.
16. Schuh Ch, Hiesmayr M, Ehrngruber T, Katz E, Neugebauer T, Adlassnig K.-P, Klement EP. Fuzzy knowledge-based weaning from artificial ventilation (Fuzzy-KBWean). In: Jamshidi M, Fathi M, Pierrot F, editors. *Proceedings of the World Automation Congress (WAC'96)*. Albuquerque: TSI Press; 1996. p. 583–8.
17. Health level seven international, HL7 Standard, http://www.hl7.org/special/Committees/arden/ products.cfm, last access: 15 August 2016.
18. Vetterlein T, Mandl H, Adlassnig, K.-P; Fuzzy Arden syntax: a fuzzy programming language for medicine. *Artificial Intelligence in Medicine* 2010; **49(1):** 1–10.
19. Samwald M, Fehre K, De Bruin J, Adlassnig K.-P. The Arden syntax standard for clinical decision support: experiences and directions. *Journal of Biomedical Informatics* 2012; **45**: 711–718.
20. Adlassnig, K.-P, Fehre K. Service-oriented fuzzy-arden-syntax-based clinical decision support. *Indian Journal of Medical Informatics* 2014; **8**(2): 75–79.