



On the use and usefulness of fuzzy sets in medical AI

Friedrich Steimann

*Institut für Technische Informatik, Rechnergestützte Wissensverarbeitung, Universität Hannover,
Appelstraße 4, D-30167 Hannover, Germany*

Accepted 1 August 2000

Abstract

Since its inception fuzzy set theory has been regarded as a formalism suitable to deal with the imprecision intrinsic to many medical problems. Based on a literature survey on the first 30 years, we investigate the impact fuzzy set theory has had on the work in medical AI and point out what it is most appreciated for. © 2001 Elsevier Science B.V. All rights reserved.

Keywords: Literature survey; Fuzzy set theory in medicine

1. Introduction

In a 1969 paper on fuzzy set theory in medicine Lotfi A. Zadeh projected that “the most likely area of application for this theory lies in medical diagnostics and, to a lesser extent, in the description of biological systems” [8]. At that time, there appeared to be some readiness among clinical researchers to invest in the new tool AI (or what it was called then) had to offer. For instance, in 1975, Kalmanson and Stegall wrote in the American Journal of Cardiology:

“Examining the circumstances that often lead modern, mechanistic cardiovascular research into areas devoid of practical significance, we suggest that our approaches, instead of our technology, are inadequate.”

and concluded, much in Zadeh’s words:

“A new conceptual and methodologic approach deserves exploration now. Based on the concept of ‘fuzzy sets’, it offers an alternative decision-making path that will allow us (and machines) to take into account the complex character of biological

E-mail address: steimann@acm.org (F. Steimann).

phenomena and thereby meet real clinical and experimental needs. One suspects that new and more precise sources of data, rather than new and more relevant ways of thinking about available data, will continue to attract attention, and so a certain degree of boldness — coupled with a willingness to face painful intellectual, ethical and even financial questions — may be necessary now. But when our rigorous sister science, mathematics, turns her attention away from precision and toward the real world of uncertainty, can we as physicians do less?” [4].

This eloquent plea falls well into the late “hype” phase of the history of fuzzy sets (as delineated by Bezdek [2]) in which expectations of its impact were still unduly high. In the meantime, we have seen a number of medically useful realizations of the theory, so that today, according to Bezdek, the “asymptote of reality” should have been reached, i.e. expectations should have settled to what can actually be delivered. To probe this asymptote of reality, we take a look at the use of fuzzy sets in medical AI as reported in the literature, and point out what it seems to be most appreciated for.

2. Some observations on the use of fuzzy sets in medical AI

Good surveys of the first 15 odd years of fuzzy set theory in medicine can be found in [1,5]. Most of the medicine-related work is indexed in the US National Library of Health’s MEDLINE, the on-line version of the Index Medicus [7]. A MEDLINE query on the free word “fuzzy” and the medical subject headings (MeSH) keyword “Fuzzy-Logic” ranging over the years 1965–1995 resulted in 191 articles dealing with the theory and application of fuzzy sets. The growth in the number of publications over the years since 1973 is shown in Fig. 1. The dramatic increase since 1992 is partly due to the fact that the keyword “Fuzzy-Logic” was only then added to the MeSH, leading to several articles whose fuzzy-relatedness is not apparent from the abstract or title, in particular, which do not contain “fuzzy” in their free text.

An analysis of the work referenced in MEDLINE reveals that fuzzy sets have been utilized for widely varying purposes, diagnosis being the most prominent from the medical point of view. The results of a more technically oriented attempt to classify the published work into the categories *classification*, *inference*, and *control*¹ reported in Fig. 1 show that approximately half of all classified publications deal with fuzzy classification, the remainder being split fairly evenly among fuzzy inference and fuzzy control. Note that, while fuzzy inference has remained almost stagnant from 1986 to 1995, fuzzy control has experienced a remarkable boom within the same period. The recent substantial increase of *classification* is correlated with the growing popularity of fuzzy neural networks, the fuzzy offshoot of neural networks (cf. Fig. 2).

¹ Admittedly, such a classification is ambiguous and should itself be fuzzy. Here, fuzzy classification includes fuzzy clustering and fuzzy pattern recognition. Fuzzy inference is defined as utilizing some kind of fuzzy *modus ponens*, while fuzzy control typically involves a feedback loop, be it open or closed. Note that systems relying on fuzzification-inference-defuzzification for other than control purposes have also been classified under inference.

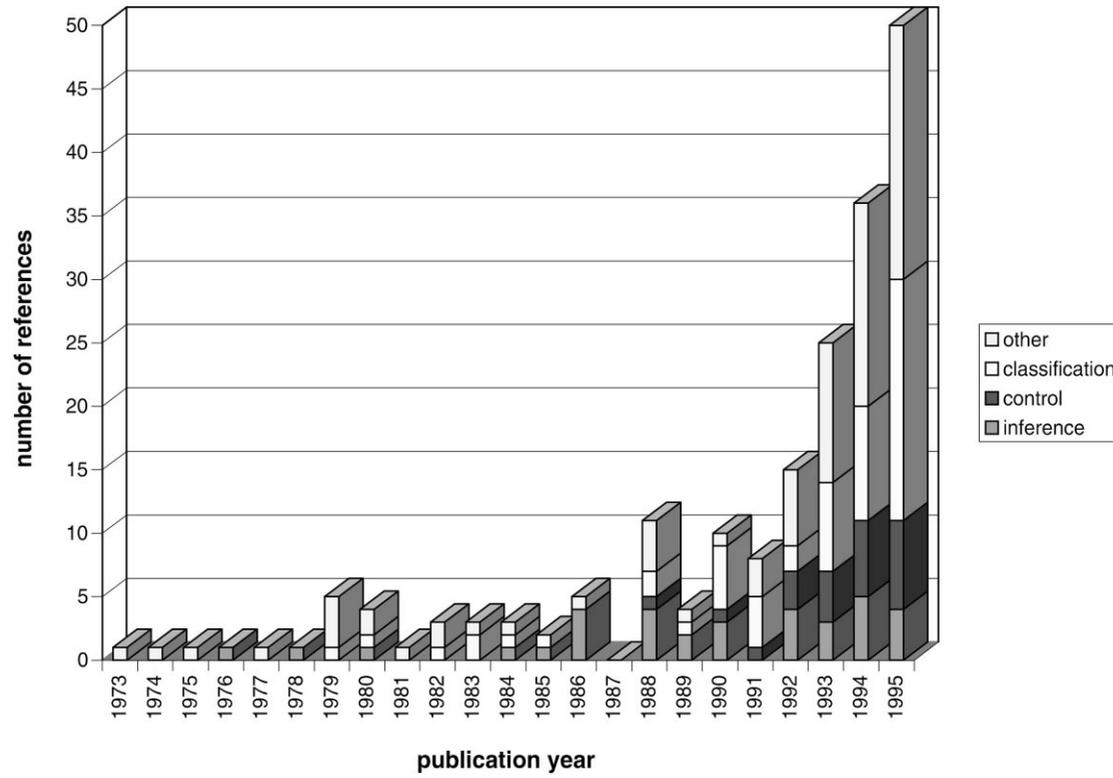


Fig. 1. Number of publications indexed in MEDLINE and dealing with fuzzy sets, classified by subject (cf. footnote 1).

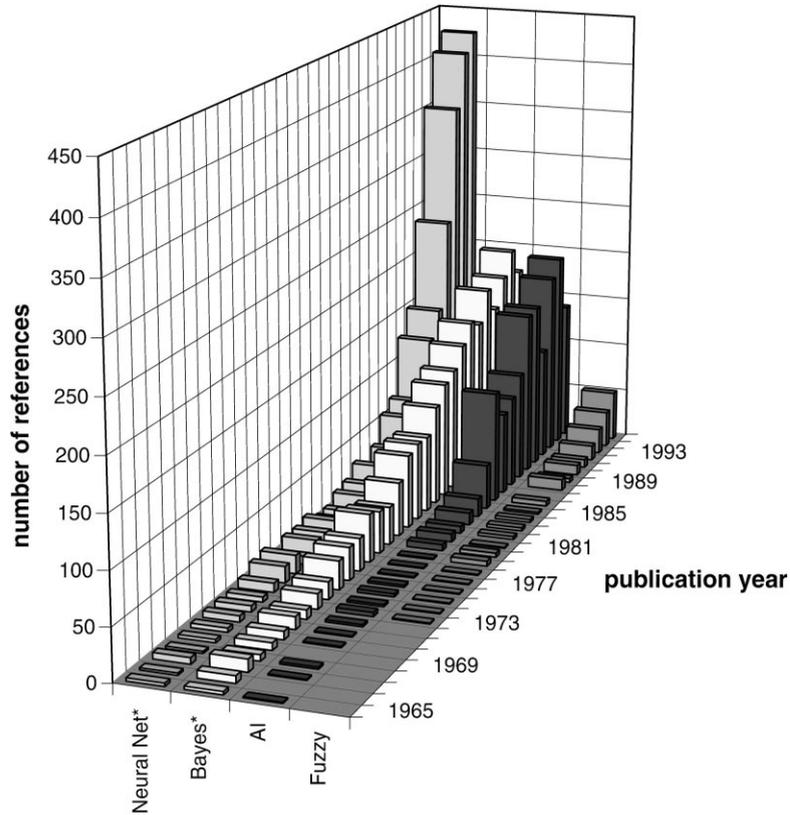


Fig. 2. Total number of publications of Fig. 1 compared to those of other formal tools aiding medicine.

Compared with the dissemination of other formal tools aiding medical decision making, it seems that the acceptance of fuzzy set theory has only been moderate. Fig. 2 contrasts the figures from Fig. 1 with the growth in the number of publications containing the keywords “artificial intelligence”, “bayes*”² and “neural net*”. Neural networks have clearly outperformed all three others. This is perhaps so because they are by nature closest to biological principles and have, therefore, attracted a lot of attention in the medical realm. A few other figures from MEDLINE just go to set the scale: the keyword “probability” resulted in almost 35,000, “computer” more than 87,000 and “statistic*” almost 218,000 matches.

Seen from the homeland of fuzzy sets, the picture is not much different: of all journal articles abstracted in the INSPEC ONDISK database from 1988–1995 [3], only 178 contain the (free) words “fuzzy” and “medic*” or “clinic*” in a medicine-related sense. As one might expect there is only little overlap between MEDLINE and INSPEC: of the

²The asterisk is a wildcard allowing an arbitrary number of characters to follow.

159 articles referenced in MEDLINE during the same period, only 37 were also included in INSPEC.

The publication years and subjects of the INSPEC articles are distributed as shown in Fig. 3. Notice that fuzzy control was not as frequently reported on in INSPEC as in MEDLINE, presumably because most fuzzy controllers currently applied in medicine bear only little technical or theoretical novelty and are thus not deemed appropriate for publishing in technical journals.

On the other hand, many of the articles with a strong theoretical bias — included in INSPEC and not in MEDLINE — make mention of medicine only as a suitable application domain. These articles typically do not report on the actual use of fuzzy sets, but point out the feasibility and the potential benefits of doing so. The practical evaluation of the ideas put forward are left to others.

3. Why fuzzy sets are considered useful for medical AI

While classical AI is discrete in nature, medicine is essentially a continuous domain. This poses immediate conflicts: if signs such as blood pressure, heart rate or blood gases are measured with (near) continuous resolution and medical actions such as the infusion rate of a drug or the setting of a ventilator can typically be varied continuously, why would one want to insist on a discrete reasoning process?

There exist, of course, good reasons for the recruitment of symbolic, that is essentially discrete, systems to solve medical problems. Historically, the necessity arose from the understanding that medical problems are often too complex and too little understood to be modeled analytically. Today, the general practicality of symbolic approaches in tackling medical problems is widely accepted and it is, to a large extent, the tacit consensus of the medical AI community that the resultant discreteness comes without detriment.³

Points can be made against this. Firstly, even if the medical actions ultimately taken are inherently discrete (a person either goes to work or stays in bed, surgery is either performed or not), their grounds are usually not: considering the fact that the final decision is made by a human anyway, there is no reason for an advice-giving system to hide or abstract away any problem-immanent gradation, particularly if the resulting discreteness is artificial. Quite the contrary, because it is much harder to overrule a clear-cut suggestion than to decide against one qualified by a degree of partial truth of, say, 0.6, discrete reasoning is likely to cause more conflict in medical decision making than its continuous counterpart.

Secondly, discretization can lead to the undue amplification of differences. Would it not seem natural that different patients with comparable symptoms be given comparable diagnoses? Yet many diagnostic systems cannot guarantee this fundamental property: due to system-immanent thresholds, similar cases may be separated during the qualitative abstraction of continuous parameters and are subsequently treated differently, possibly resulting in significantly differing diagnoses. Such a behavior will be perceived as arbitrary

³ Discretization is, of course, inevitable when interfacing a digital computer. In AI, however, discreteness refers to a rather coarse partitioning of a continuous scale. The negative side-effects of such a discretization can be lessened by choosing a higher resolution, albeit only at the price of increased complexity.

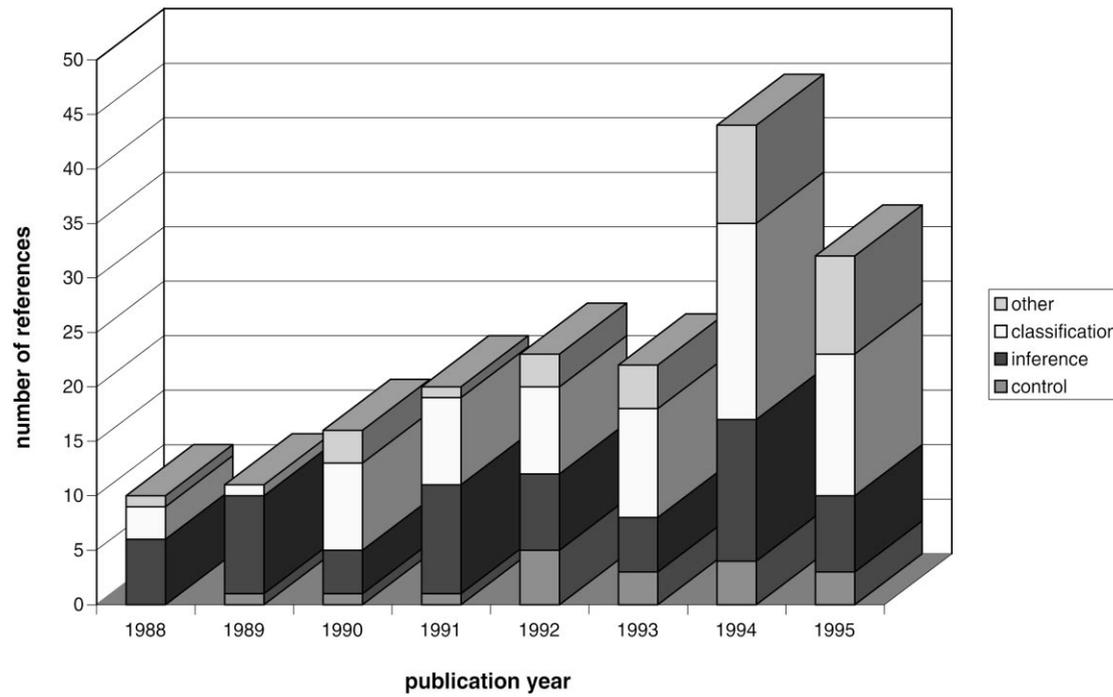


Fig. 3. Number of publications on medical or clinical applications of fuzzy sets contained in the INSPEC ONDISK database.

and is likely to provoke disapproval during evaluation and routine employment. This is so because intuitively, whenever comparable cases fall into different categories, there is strong indication that something has gone wrong. This observation is so fundamental that automated verification techniques have been based thereon.

Analogously and thirdly, discreteness may cause erratic behavior in the context of change. Would it not seem likely that a slight alteration over time in the vital parameters of one patient changes the diagnosis only slightly? Instead, however, discrete dynamic systems usually respond to the continuous change in the patient's condition with an abrupt change in state. Yet, all one would expect is the materialization of the mathematical definition of continuity: informally stated, a system is continuous if it maps close inputs to close outputs.

Most of the medical fuzzy systems described in the literature do just that: they map close inputs to close outputs. Fuzzy classifiers allow multiple gradual class membership and, therefore, the smooth transition from one class to the other as the input changes. Fuzzy control reacts to any deviation from the control target with a proportionate countermeasure. And fuzzy inference systems, explicating the gradation that is implicit in the meaning of their symbols, propagate the varying degrees of match of the input with these symbols along their inference chains to the output where they serve to qualify the results of reasoning.

It seems that the medical AI community has recognized fuzzy sets most for their “ability to introduce notions of continuity into deductive thinking” [6]. Because it is continuous, the behavior of fuzzy systems is likely to be closer to medical reality than that of their categorical counterparts. At the same time, fuzzy sets allow one to fully enjoy the ease of expression offered by symbolic models and their formalisms, avoiding the unwieldiness of the analytical alternatives. Fuzzy sets can bridge the gap between the discrete world of reasoning and the continuity of reality; today, this appears to be the main reason why they are considered useful.

Acknowledgements

The author's work has in part been supported by the Universitätsgesellschaft Hildesheim e.V.

References

- [1] Adlassnig KP. A survey on medical diagnosis and fuzzy subsets. In: Gupta MM, Sanchez E, editors. Approximate reasoning in decision analysis. Amsterdam: North-Holland, 1982. pp. 203–217.
- [2] Bezdek JC. Fuzzy models — what are they and why? *IEEE Trans Fuzzy Syst* 1993;1:1–6.
- [3] INSPEC ONDISK database. IEE, London, 1986–1996.
- [4] Kalmanson D, Stegall HF. Cardiovascular investigations and fuzzy set theory. *Am J Cardiol* 1975;35:80–4.
- [5] Maiers JE. Fuzzy set theory and medicine: the first twenty years and beyond. In: Proceedings of the 9th Symposium on Computer Applications in Medical Care. IEEE, 1985. pp. 325–329.
- [6] Martin JF. Fuzzy control in anaesthesia. *J Clin Monitoring* 1994;10:77–80.
- [7] MEDLINE Express. US National Library of Medicine, 1966–1995.
- [8] Zadeh LA. Biological application of the theory of fuzzy sets and systems. In: Proceedings of the International Symposium on Biocybernetics of the Central Nervous System. Boston: Little, Brown & Co., 1969. pp. 199–212.