Applying Fuzzy Logic to Medical Decision Making in the Intensive Care Unit

Jason H. T. Bates and Michael P. Young

Pulmonary and Critical Care Division, Department of Medicine, University of Vermont and Fletcher Allen Health Care, Burlington, Vermont

Intensive care medicine frequently involves making rapid decisions on the basis of a large and disparate array of information. To make medical decisions, intensive care unit (ICU) physicians often rely on conventional wisdom and personal experience to arrive at subjective assessments and judgments. This requires an intuitive, or nonexplicit weighting of various factors to achieve an optimal balance between clinical endpoints that are often competing. Recently there has been heightened concern over the burden of unwanted variation in clinical practice (1–3). As a result, physicians are increasingly being asked to adhere to explicit guidelines that have been agreed on by the medical community at large (4). Such guidelines often have a logical structure that makes them suitable for computer implementation. Consequently, there is increasing interest in computer-based decision support tools to automate aspects of the medical decision making that takes place in complex clinical areas such as the ICU (5). An example is specifying the conditions under which a patient might be successfully weaned from mechanical ventilation (6, 7).

Compared with the human brain, computers are well suited to making rapid calculations and recalling large numbers of facts, permitting the creation of decision networks that support near limitless complexity. For many situations, however, the variable nature of disease and patient characteristics makes it difficult, even impossible, to decide exactly what should be done in every conceivable set of circumstances. In such situations, the physician must depend on intuitive decision making, sometimes described as the art of medicine. Intuitive decision making is usually described as being poorly suited to computerization. Certainly, subjective judgment generally defies description in terms of the kinds of deterministic mathematical equations that computers are well suited to solving. However, the methods of fuzzy logic are suited to this kind of endeavor and can lead to algorithms that mirror the nonexplicit nature of clinical decision making (5, 8, 9).

In this Perspective, we will describe how fuzzy logic works by illustrating its application in a simplified model of fluid resuscitation of ICU patients. After clinicians appreciate the kinship of fuzzy logic with expert clinical thinking, we anticipate that fuzzy logic may become widely embraced for use in some aspects of clinical decision making.

FUZZY LOGIC

Fuzzy logic was introduced by Zadeh in the 1960s (8, 10–12) and is now well established as an engineering discipline (12–14). Fuzzy logic is used for controlling a wide variety of devices (13, 14). Fuzzy logic has been used in applications that are amenable to conventional control algorithms on the basis of mathematical models of the system being controlled, such as the high-frequency mechanical ventilator of Noshiro and coworkers. (15). However, fuzzy logic has a particular advantage in areas where precise mathematical description of the control process is impossible and is thus especially suited to support medical decision making (5). We have previously developed a fuzzy logic–based approach to the automatic control of pressure support mechanical ventilation for ICU patients (16, 17). However, the utility of fuzzy logic in the ICU is by no means limited to this particular application. Fuzzy logic has also been applied, for example, to the problem of controlling fluid recuscitation (18, 19). In this article, we use a simplified example drawn from the latter application to demonstrate how fuzzy logic can be used in clinical applications.

Control of Intravenous Fluid Resuscitation

The rate at which intravenous fluids are administered to a patient in the ICU is currently determined by the physician. There are multiple factors that clinicians try to weigh as they determine the amount and rate of intravenous fluid administration that should be administered to a given patient. However, to illustrate how fuzzy logic control works we will consider only two variables: mean arterial blood pressure (MAP) and hourly urine output (HUO). With given hourly measurements of MAP and HUO, how should intravenous fluid rate (IFR) be adjusted each time measurements are made? The general rules applicable to this problem are obvious: if MAP and HUO are both high, then IFR needs to be reduced, and if MAP and HUO are low, then IFR should be increased. It is more difficult to be specific, however, about exactly what the IFR should be for any given pair of values of MAP and HUO. The problem could be solved if there were a mathematical equation that calculated an exact value of IFR for any given values of MAP and HUO. Unfortunately, such an equation does not exist. Deriving one may not be possible. An alternative approach is to seek a purely empirical equation by modeling common ICU practice patterns. In essence, this is what fuzzy logic does.

Fuzzy Sets

The first step in implementing a fuzzy logic control algorithm is to "fuzzify" the measured variables. This can be done for MAP and HUO as follows. Considering MAP first, we note that this quantity may be either too high, acceptable, or too low, so we will divide its range of possible values into three corresponding

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Correspondence and requests for reprints should be addressed to Jason H. T. Bates, Ph.D., HSRF, Room 228, University of Vermont, 149 Beaumont Avenue, Burlington, VT 05405-0075. E-mail: jhtbates@zoo.uvm.edu

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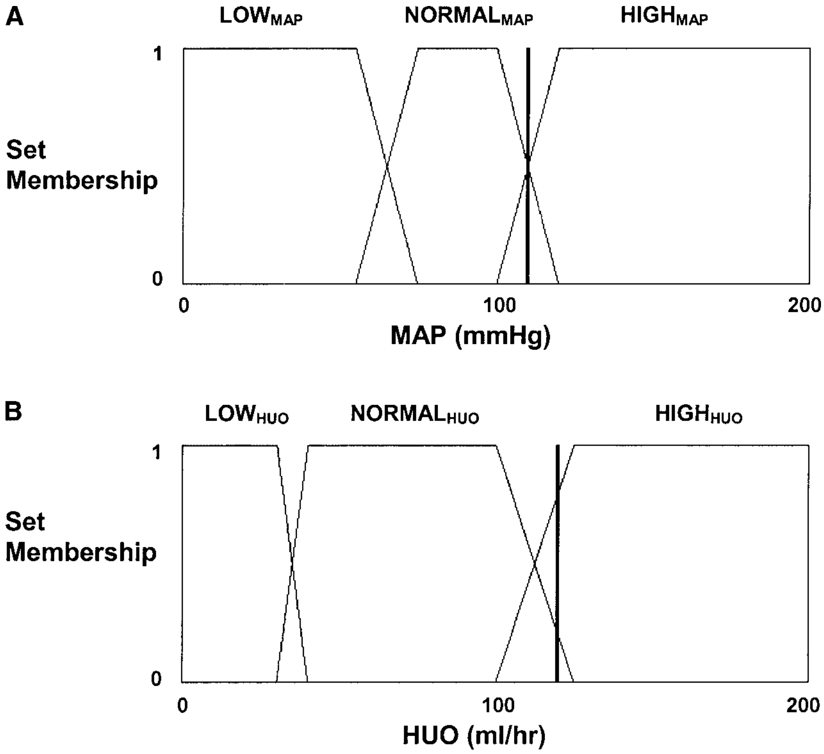

Figure 1. Fuzzy sets for (*A*) mean arterial blood pressure (*MAP*) and (*B*) hourly urine output (*HUO*). The two variables have each been divided into three overlapping sets labeled *LOW*, *NORMAL*, and *HIGH*. The *vertical line* in (*A*) represents a measurement of MAP of 110 mm Hg, which has a membership level of 0.5 in both the *NORMAL* and *HIGH* sets. The *vertical line* in (*B*) represents a measurement of *HUO* of 120 ml/hour, which has a membership level of 0.2 in the *NORMAL* set and 0.8 in the *HIGH* set.

fuzzy sets. Starting with the set corresponding to acceptable values for MAP, we first ask what range of values for MAP would be designed unquestionably normal. Let this be 75 to 100 mm Hg (not everyone might agree with this, so this choice merely captures the experience of one particular "expert"). We thus create a fuzzy set labeled NORMAL$_{MAP}$ and assign values of MAP between 75 and 100 mm Hg to a membership level of 1.0 in this set (Figure 1).

Now we address the more vague issue of what range of values for MAP could possibly be normal but might also be abnormal. Let this be 100 to 120 mm Hg at the upper end and 55 to 75 mm Hg at the lower end. In other words, if MAP is above 120 mm Hg it is unquestionably too high, whereas between 100 and 120 mm Hg it could go either way. Similarly, if MAP is below 55 mm Hg it is without doubt too low, whereas between 55 and 75 mm Hg there is some doubt about whether it is normal or too low. These uncertainties are represented by membership levels in NORMAL$_{MAP}$ that decrease linearly from 1.0 at the inner boundaries of the uncertain regions down to 0 at the outer boundaries (Figure 1). We can construct LOW$_{MAP}$ and HIGH$_{MAP}$ fuzzy sets in a similar manner. These begin at the inner boundaries of the uncertain regions with membership levels of zero and proceed linearly up to membership levels of 1.0 at the outer boundaries, precisely the converse of the situation for NORMAL$_{MAP}$. Above 120 mm Hg we have already established that MAP is too high, so values greater than 120 mm Hg have a membership level of 1.0 in HIGH$_{MAP}$ as well as for values of MAP below 55 mm Hg in LOW$_{MAP}$. There is no absolute rule that says the uncertain parts of the fuzzy sets must ascend or descend linearly. However, it is important that the various set memberships always add to unity for every value of the fuzzy variable because membership values essentially represent probabilities of set membership. Straight lines are the most straightforward way of achieving this condition.

A key aspect of the fuzzy sets as depicted in Figure 1A is that they overlap. In this example, although there are some ranges of MAP for which the classification of high, normal, or low is unequivocal, there are also two regions where classification is uncertain. A value of MAP in one of these regions thus has membership in two sets simultaneously, with the respective levels of membership reflecting the likelihood of belonging to either set. For example, a MAP of 110 mm Hg has a membership in NORMAL$_{MAP}$ of 0.5 and a membership in HIGH$_{MAP}$ of 0.5 (*see* vertical line in Figure 1A), with the two membership levels always adding to 1.0. The definitions of these sets are thus related to the probability of a certain value of MAP receiving a certain classification. If these probabilities are known then the sets can be defined accordingly. However, it is also possible to define the fuzzy sets on the basis of a "gut feeling." In other words, it is not necessary to formally determine classification probabilities—the sets in Figure 1A can just as readily be defined on the basis of an expert's experience and intuition. Of course, we could have defined a larger number of overlapping fuzzy sets, for example, five sets denoted VERY HIGH, HIGH, NORMAL, LOW, and VERY LOW. However, for the purposes of this example, the three sets shown in Figure 1A are sufficient.

The fuzzification process of defining sets for MAP described previously can also be applied to the other variable of interest, namely HUO, as shown in Figure 1B. Here again, we define three overlapping fuzzy sets labeled LOW$_{HUO}$, NORMAL$_{HUO}$, and HIGH$_{HUO}$, each characterized by their respective regions of certainty (membership level 1.0) and uncertainty (membership level between 0 and 1.0). The ranges of HUO over which the LOW$_{HUO}$, NORMAL$_{HUO}$, and HIGH$_{HUO}$ sets have membership of unity are, respectively, 0 to 30, 40 to 100, and 125 to 200 ml/hour.

Rule Tables

With the sets suitably fuzzified, we are now in a position to define the clinical status of a patient each time a pair of new measurements of MAP and HUO arrives. Each pair of measurements leads to one or more pairs of set memberships. For example, in the case of the example shown in Figure 1 with MAP = 110 mm Hg

TABLE 1.

	MAP		
HUO	Low	Normal	High
Low	very high	moderate	low
Normal	high	maintain	low
High	moderate	maintain	low

Definition of abbreviations: HUO = hourly urine output; MAP = mean arterial blood pressure.

Rule table for deciding what action should be taken (i.e., how intravenous fluid rate should be changed) for any pair of fuzzy set memberships for MAP (Figure 1A) and HUO (see also Figure 1B).

and HUO = 120 ml/hour there is finite membership in the set combinations $NORMAL_{MAP}$ and $NORMAL_{HUO}$, $NORMAL_{MAP}$ and $HIGH_{HUO}$, $HIGH_{MAP}$ and $NORMAL_{HUO}$, and $HIGH_{MAP}$ and $HIGH_{HUO}$. The next step is to decide what action should be taken for each combination of set memberships. This question is again addressed in general terms using intuitive notions. Some situations are obvious. For example, if MAP is normal and HUO is normal then IFR should clearly be set at a normal maintenance level. Similarly, if MAP is high and HUO is high then IFR should set to a low level. The way to deal with certain other combinations may be a little less clear, such as when MAP is high and HUO is normal. One expert might argue that this situation calls for a maintenance level of IFR, whereas another might require IFR to be set below the maintenance level. In any case, we must build up a rule table specifying what should be done for every possible combination of fuzzy set memberships for MAP and HUO. For the purposes of this illustration, we will designate five categories of IFR labeled LOW, MAINTENANCE, MODERATE, HIGH, and VERY HIGH. The various membership combinations for MAP and HUO are assigned to these categories as shown in Table 1.

Calculating the Action to Be Taken

The rules specified in Table 1 might make intuitive sense, but for them to be implemented in any given patient it is necessary to have some way of transforming terms like HIGH and LOW into precise changes in IFR in terms of ml/hour. Only then can an assessment of clinical status be translated into a specific action. This is again achieved with the use of fuzzy sets but now applied to IFR. Although the categories of IFR used in Table 1 do not mean anything precise in an absolute sense, we can still fuzzify IFR in a way that seems reasonable. Figure 2 shows an example where we have decided that IFR is definitely within the MAINTENANCE range between 100 and 200 ml/hour and that the MAINTENANCE classification might possibly extend to as much as 400 ml/hour and to as little as 60 ml/hour. The other four fuzzy sets are established using similar considerations. Of course, not everyone will agree with this particular fuzzification, but that merely illustrates the power of the fuzzy set concept. Different experts may fuzzify IFR somewhat differently in ways that reflect their respective experiences or the particular patient group they are dealing with.

Now we are ready for the final step. Again consider the example shown in Figure 1 where MAP is 110 mm Hg and HUO is 120 ml/hour. This leads to fuzzy set memberships of 0.5 in $NORMAL_{MAP}$, 0.5 in $HIGH_{MAP}$, 0.2 in $NORMAL_{HUO}$, and 0.8 in $HIGH_{HUO}$. Invoking every pair combination of these sets in the rule table (Table 1) gives the following actions:

$$NORMAL_{MAP} \text{ and } NORMAL_{HUO} = MAINTAIN_{IFR}$$

$$NORMAL_{MAP} \text{ and } HIGH_{HUO} = MAINTAIN_{IFR}$$

$$HIGH_{MAP} \text{ and } NORMAL_{HUO} = LOW_{IFR}$$

$$HIGH_{MAP} \text{ and } HIGH_{HUO} = LOW_{IFR}$$

The final action is clearly going to be some weighted sum of these four actions. The question is, how should each weighting factor be chosen? As each action is derived from two set membership values, it would seem logical to choose its weighing factor on the basis of some function of these set memberships. Furthermore, we are developing a feedback control algorithm, so the stability of the algorithm is a major consideration. As a conservative response tends to favor stability, we choose the smallest of the two set memberships as the weighting factor. Thus, for example, one of the actions LOW_{IFR} came from memberships of 0.5 in $HIGH_{MAP}$ and 0.2 in $HIGH_{HUO}$, so this LOW_{IFR} action receives a weighting of 0.2.

These weighting factors are finally converted into a "crisp" value of IFR as indicated in Figure 2, where each of the fuzzy action sets has been shaded to a level equal to its weighting factor. A question arises as to what to do if an action set is invoked more than once, as occurs in this example with both LOW_{IFR} and $MAINTAIN_{IFR}$. Algorithm stability is still an issue, of course, but the weighting factors of the action sets were already determined conservatively in the manner described in the preceding paragraph. We therefore use the largest of the weighting factors for each of LOW_{IFR} and $MAINTAIN_{IFR}$. This defines a polygonal shape (the shaded region in Figure 2) whose centroid gives the precise value of IFR to be applied to the patient. In the case of this example, the value of IFR to be applied is 145 ml/hour.

We thus have an algorithm for translating precise measurements of MAP and HUO into a precise change in IFR that could, in principle, be implemented completely automatically without human intervention. Furthermore, developing this algorithm did not require us to first define a precise relationship between MAP, HUO, and IFR that could be written down in terms of a mathematical equation, which might be extremely difficult. Instead, we have an algorithm that is very simple and appears to operate in a manner similar to human subjective judgment. Exactly how the algorithm behaves, of course, is a function of how the fuzzy sets for MAP, HUO, and IFR and the rule table are defined. Different experts would probably define these in different ways, and the resulting algorithms would perform accordingly. Fuzzy logic thus has the ability to capture the experience-based expertise of a particular individual and code it as an algorithm. A computer program implementing the previous example of fuzzy logic is available for downloading from the online supplement. Readers are invited to define their own fuzzy sets for MAP, HUO, and IFR, together with the rule table entries, and experiment with the behavior of the algorithm for various values of MAP and HUO.

Of course, the aforementioned algorithm is too simplistic for clinical use. However, it is easy to see how the algorithm could be extended to include additional fuzzy variables such as heart rate or central venous pressure. The rates of change of MAP and HUO could also be obtained by taking differences between successive hourly measurements. These rates of change could be fuzzified into sets such as DECREASING, STABLE, and INCREASING and would serve to indicate the trend in a patient's fluid status. This would allow more precise control of fluid balance. Of course, for each additional variable there is a substantial increase in algorithm complexity because the rule table gains an additional dimension, so many more scenarios must be considered. A balance, therefore, needs to be struck between the number of independent fuzzy variables used and the number of fuzzy sets for each variable versus the precision of control achieved.

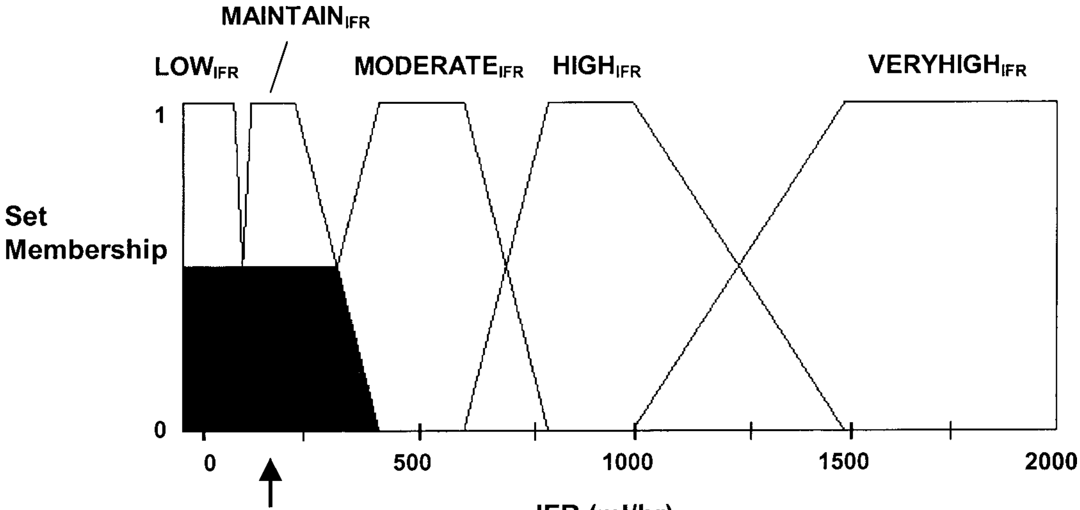

Figure 2. The controlled quantity, intravenous fluid rate (*IFR*), is divided into five overlapping fuzzy sets. The set memberships arising from the measurements of MAP and HUO indicated in Figure 1 give rise to membership levels in the IFR sets indicated by the *shaded region*. The centroid of this region is indicated by the *vertical arrow* and is the final "crisp" value of IFR to be implemented in the patient. The ranges of IFR for which the five fuzzy sets have membership of unity are, in ascending order, −60 to 60, 100 to 200, 400 to 600, 800 to 1000, and 1500 to 2000 ml/hour. (Note that the lower limit of −60 ml/hour for the LOW set, although by itself physically meaningless, means that the centroid of the lowest set is just above zero. This allows for a very low IFR if only the LOW set is invoked.)

We must also be aware that the basic assumption behind any control algorithm is that there is sufficient information contained in the input variables to achieve adequate control of the output variable. Medical decisions based on fuzzy logic will only succeed in so far as this is the case. For example, if the appropriate IFR for a patient depends on data other than those expressed by MAP and HUO, then the algorithm we developed previously will not work. It may be impossible to say *a priori* whether or not a given set of input variables contains sufficient information for a given application due to the complex and nonlinear nature of biological systems. Thus, rigorously validating the effectiveness of algorithms on the basis of fuzzy logic will require testing them in clinical trials on patients.

As a final point, it is interesting to consider how a fuzzy logic algorithm for controlling fluid balance might be implemented in practice. It could be done with minimal capital outlay by having a human operator periodically enter MAP and HUO values into a personal computer. Intravenous fluid flow could then be manually adjusted according to the resulting fuzzy logic calculation. However, automating the process would greatly increase both reliability and savings in labor. Automation would require the following series of steps: (*1*) MAP and HUO would be measured at regular intervals by suitable transducers (such as a urine container placed on an electronic scale), (*2*) the values of MAP and HUO would be acquired by a computer, (*3*) the fuzzy calculations would be made, and (*4*) the computer would control the fluid delivery rate from a motorized dispenser. Realizing these various steps is an engineering problem, readily soluble given sufficient resources.

OTHER APPLICATIONS

We recently used fuzzy logic to devise an algorithm for controlling the level of pressure support ventilation in patients in the ICU with chronic obstructive pulmonary disease (16, 17). This algorithm is rather more complicated than the contrived example described previously; it uses six variables instead of only two and incorporates an additional intermediate step before arriving at the final decision about how to adjust the pressure support ventilation level. However, the principles of set fuzzification, rule table generation, and determination of action are precisely the same as in the simple example outlined previously. The algorithm was tested retrospectively on 13 patients with severe chronic obstructive pulmonary disease. The algorithm made recommendations that were generally compatible with those actually implemented in the patients (16), with agreement occurring in a large fraction of cases. In those cases in which the algorithm did not agree with what was actually done, the differences between recommended and applied changes in pressure support ventilation levels were mostly small (less than 2 cm H_2O). Disagreements of this nature would be expected even between different physicians because of the indeterminate and subjective nature of the weaning process. Indeed, the performance of the fuzzy algorithm depends greatly on whose expertise it encapsulates (i.e., who fuzzified the parameters and set up the rule tables). Thus, we would expect some disagreement even between different realizations of the same fuzzy algorithm produced by different experts. The algorithm was also tested prospectively on a small number of patients with chronic obstructive pulmonary disease (17) and was shown to be capable of maintaining pressure support ventilation levels within a clinically reasonable range.

Fuzzy logic has also seen application in other areas of medicine, such as anesthesia (20). Schaublin and coworkers (21) used fuzzy logic to control VT and ventilatory frequency during anesthesia in an attempt to maintain $P_{ET_{CO_2}}$ at a predetermined level. By measuring $P_{ET_{CO_2}}$ together with its rate of change and determining updated values for VT and frequency every 10 seconds, they were able to achieve a control of $P_{ET_{CO_2}}$, which was as good as that achieved by a human controller. Mason and coworkers (22, 23) used a fuzzy logic algorithm that could learn from experience to control the administration of neuromuscular blockade during surgery. Blood pressure has been used for control of depth of anesthesia by fuzzy logic (24, 25), and in some cases outperformed a human operator (25). However, despite these studies and others (4, 9, 26, 27) showing generally promising results, the literature on fuzzy logic applications in medicine remains modest. In our opinion, this is a largely untapped area that holds great promise for increasing the efficiency and reliability of health care delivery. We believe that greater effort should be applied to the exploration of ways to apply fuzzy logic in medical decision making.

We have thus far considered fuzzy logic as a means of getting a machine to take over some activity currently performed by a human operator. Although this may be the most obvious application area for fuzzy logic, it does require that the appropriate mode of action for a given situation be known. Unfortunately, although the best practice may be universally agreed on in some areas of medicine, this is by no means always the case. Examples abound of situations requiring a medical decision for which there is no established algorithm (e.g., weaning patients from mechanical ventilation). A fuzzy logic algorithm operating in such an area is only as good as the expertise of the individual who defined its fuzzy sets and rule table entries. This may be useful if the individual concerned is recognized as an expert, but it does not guarantee that the algorithm will make correct decisions. This raises the interesting possibility that fuzzy logic may have application as a means of investigating variations in clinical practice patterns. For example, one could have different ICU physicians parameterize a fuzzy logic algorithm for intravenous fluid administration according to their individual inclinations. The resulting collection of algorithms could then be subjected to a range of patient scenarios. This would permit quantitative assessment of the degree of variation between physicians. At present, the only means of doing this is by observing the actions of the physicians themselves as they treat real patients, which is both time consuming and expensive. A similar approach could be used for the comparison of different weaning protocols, which currently must be done through clinical trials (28).

FINAL COMMENTS

Fuzzy logic provides a means for encapsulating the subjective decision making process in an algorithm suitable for computer implementation. As such, it appears to be eminently suited to aspects of medical decision making. Furthermore, the principles behind fuzzy logic are straightforward and its implementation in software is relatively easy. Nevertheless, the applications of fuzzy logic in medicine are few. Our perspective on this state of affairs is that more clinicians need to be made aware of what fuzzy logic is. More research is needed before we can even begin to understand the potential applications of fuzzy logic in medicine. This research will have to be undertaken in a series of steps, beginning with development of a fuzzy logic algorithm for a given application, followed by testing of the algorithm on hypothetical test cases, and eventually leading to validation in patients. This can be complicated and time consuming but may eventually result in procedures for formalizing medical decision making that will reduce unwanted variation in clinical practice. In addition, fuzzy logic may support the automation of some types of devices used in the delivery of health care services.

References

1. Wennberg J, Cooper MM, editors. The Dartmouth atlas of medical care in the United States: a report on the medicare program. Chicago, IL: AHA Press; 1999.
2. Kohn L, Corrigan J, Donaldson M, editors. To err is human: building a safer health care system. Committee on Quality of Health Care in America, Institute of Medicine. Washington, DC: National Academy Press; 2000.
3. Agency for Healthcare Research and Quality. Making health care safer: a critical analysis of patient safety practices. Rockville, MD: AHRQ Publications; 2001.
4. Eddy DM. Clinical decision making from theory to practice: a collection of essays from the Journal of the American Medical Association. Sudbury, MA: Jones and Bartlett; 1996.
5. Hanson CW, Marshall BE. Artificial intelligence applications in the intensive care unit. *Crit Care Med* 2001;29:427–435.
6. Brochard L, Rauss A, Benito S, Conti G, Mancebo J, Rekik N, Gasparetto A, Lemaire F. Comparison of three methods of gradual withdrawal from ventilatory support during weaning from mechanical ventilation. *Am J Respir Crit Care Med* 1994;150:896–903.
7. Dojat M, Harf A, Tochard D, Laforest M, Lemaire F, Brochard L. Evaluation of a knowledge-based system providing ventilatory management and decision for extubation. *Am J Respir Crit Care Med* 1996; 153:997–1004.
8. Steimann F. On the use and usefulness of fuzzy sets in medical AI. *Artif Intell Med* 2001;21:131–137.
9. Helgason CM, Jobe TH. Causal interactions, fuzzy sets and cerebrovascular 'accident': the limits of evidence-based medicine and the advent of complexity-based medicine. *Neuroepidemiology* 1999;18:64–67.
10. Zadeh LA. Fuzzy sets. *Information and Control* 1965;8:338–352.
11. Cox E. Fuzzy fundamentals. *IEEE Spectrum* 1992;Oct:58.
12. Hess J. Fuzzy logic and medical device technology. *Med Device Technol* 1992;Oct:37.
13. Sugeno M. Industrial applications of fuzzy control. Amsterdam: North-Holland; 1985.
14. Yager RR, Filev DP. Essentials of fuzzy modeling and control. New York: Wiley-Interscience; 1994.
15. Noshiro M, Matsunami T, Takakuda K, Ryumae S, Kagawa T, Shimizu M, Fujino T. Fuzzy and conventional control of high-frequency ventilation. *Med Biol Eng Comput* 1994;32:377–383.
16. Nemoto T, Hatzakis G, Thorpe CW, Olivenstein R, Dial S, Bates JHT. Automatic control of pressure support ventilation using fuzzy logic. *Am J Respir Crit Care Med* 1999;160:550–556.
17. Bates JHT, Hatzakis G, Olivenstein R. Fuzzy logic and mechanical ventilation. *Respir Care Clin N Am* 2001;9:363–377.
18. Hanson CW, Weiss Y, Frasch F, Marshall C, Marshall BE. A fuzzy control strategy for postoperative volume resuscitation. *Anesthesiology* 1998;89(Suppl 3A):A475.
19. Chan W, Naghdy F. Prognosis of body fluid level by fuzzy logic technique. *Methods Inf Med* 2001;40:52–58.
20. Martin JF. Fuzzy control during anesthesia. *J Clin Monit* 1994;10:77–80.
21. Schaublin J, Derighetti M, Feigenwinter P, Petersen-Felix S, Zbinden AM. Fuzzy logic control of mechanical ventilation during anesthesia. *Br J Anaesth* 1996;77:636–641.
22. Mason DG, Ross JJ, Edwards ND, Linkens DA, Reilly CS. Self-learning fuzzy control of atracurium-induced neuromuscular block during surgery. *Med Biol Eng Comput* 1997;35:498–503.
23. Mason DG, Ross JJ, Edwards ND, Linkens DA, Reilly CS. Self-learning fuzzy control with temporal knowledge for atracurium-induced neuromuscular block during surgery. *Comput Biomed Res* 1999;32:187–197.
24. Tsutsui T, Arita S. Fuzzy-logic control of blood pressure through enflurane anesthesia. *J Clin Monit* 1994;10:110–117.
25. Zbinden AM, Feigenwinter P, Petersen-Felix S, Hacisalihzade S. Arterial pressure control with isoflurane using fuzzy logic. *Br J Anaesth* 1995; 74:66–72.
26. Ohayon MM. Improved decisionmaking processes with the fuzzy logic approach in the epidemiology of sleep disorders. *J Psychosom Res* 1999; 47:297–311.
27. Velasevic DM, Saletic DZ, Saletic SZ. A fuzzy sets theory application in determining the severity of respiratory failure. *Int J Med Inf* 2001; 63:101–107.
28. Esteban A, Frutos F, Tobin MJ, Alia I, Solsona JF, Valverdu I, Fernandez R, de la Cal MA, Benito S, Tomas R. A comparison of four methods of weaning patients from mechanical ventilation. *N Engl J Med* 1995;332: 345–350.