Fuzzy Logic, Sharp Results?

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The study by Shiomi et al. (*1*) used fuzzy reasoning to improve interpretation of liver/spleen scintigrams. Although fuzzy reasoning was invented in the United States (*2*), it has, until recently, received rather scant attention in this country. Indeed, the theory has been largely ignored if not outright rejected as intellectually unsound (*3*). Recently, however, fuzzy logic has had an extremely different reception in Japan, where it quickly became a mainstream theory and was theory became and was utilized in everything from the design of efficient subway systems, steady-shot camcorders, one-button washing machines to large scientific (LIFE) and biomedical projects. It has also found a place in the development of medical diagnostic algorithms. The travails of fuzzy reasoning, its battle for acceptance and the fate of its proponents, is one of the best examples of paradigm shift in science and a graphic illustration of the scientific revolution as suggested by Kuhn (*4*).

The fundamental premise of fuzzy reasoning is that distinctions between values in different categories in the real world are not crisp. For example, if the normal range for creatine kinase in a laboratory test for acute myocardial infarction is 110 to 180 U, the value of 181 U would conventionally be regarded as a positive test, while a value of 179 U would be considered a negative. It is not unusual to hear discussions in which a patient is considered to be "ruled in" or "ruled out" based on trivial differences in numbers that happen to fall on different sides of the sharp fence. The situation becomes even more difficult when image interpretation is involved. Qualitative assessment of nuclear scans or other radiological images is open to a number of biases, including the knowledge and interpretation of clinical history, variations in the use of diagnostic criteria, differences in the perception of abnormalities, image quality and characteristics of display systems, as well as many others (*5–9*). Thus, a recent study of mammogram interpretation documented vast differences in the reading of diagnostic abnormalities among experienced radiologists and demonstrated significant differences in perception and interpretation of identical images (*10*). Although quantification has been introduced in a number of nuclear procedures, its impact on diagnostic reasoning has not been evaluated. As with most laboratory testing, quantitative analysis of thallium scintigrams, for example, relies on sharp distinctions between "normal" and "abnormal," thus becoming subject to the same limitations as all other "sharp" diagnostic modalities.

DEGREE OF MEMBERSHIP

Fuzzy reasoning introduces a notion of degree of membership expressed as a number in the interval from 0 to 1 to remedy problems associated with sharply described datasets. Thus, a laboratory value slightly exceeding the "normal" range might be considered as a 0.9 member of the "normal" set, while a number twice the limit might be considered a 0.3 member. One of the key criticisms of fuzzy reasoning is the arbitrary nature of assigning the degree of membership. Indeed, no theory allows one to say whether, using our example, CK of 250 U is a 0.6 member of the normal set or 0.3 member. Such fuzzy assignments, however, are the daily fare in clinical medicine and physicians become remarkably good at guessing membership functions. Most importantly, however, the exact assignments of membership values do not matter much in fuzzy reasoning.

DIAGNOSTIC CLINICAL REASONING

To date, most diagnostic clinical reasoning has been modeled on Bayesian analysis, in which estimates of posterior probabilities are based on the prevalence of events and prior probability. Fuzzy reasoning, however, provides a much more intuitive way of handling imprecise data, and modeling diagnostic reasoning using fuzzy reasoning may provide a much closer approximation of clinical reality. Most physicians would say "this result is somewhat abnormal" rather than "this result has a 30% probability of being correct." The article by Shiomi et al. (*1*) on fuzzy sets in liver spleen scanning presents just such a way of structuring clinical judgment. A paradigm which has been

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useful for diagnostic testing in the past is that patients fall into distinct diagnostic categories. While such sharp distinctions between different syndromes have aided in developing modern academic medicine greatly, they have also tended to generate unrealistic expectations of accuracy in diagnostic testing. Now that nuclear medicine tests are being used increasingly to aid in selecting therapy and not just in identifying a diagnosis, it makes less sense to consider rigid disease categories. Fuzzy reasoning modeling may also provide a better description of the patient's disease state and perhaps integrate the art of medicine with its science.

METHODOLOGICAL STRENGTHS AND LIMITATIONS

The strength of the Shiomi et al. method (1) is that various features of the liver/spleen scintigram, e.g., splenomegaly, are represented as fuzzy sets, which provide a realistic model for these features. For example, a borderline enlarged spleen may just as likely be a member of the set of normal spleens as the set of enlarged spleens. Allowing it to be partially in both sets provides a good model for the real clinical situation. Shiomi et al. used several variables from the liver/spleen scintigram in the diagnosis of chronic liver disease. This method could be extended to include features of other laboratory or imaging tests, or even history and physical findings in a diagnostic algorithm. Inclusion of other variables would extend this system's utility as a medical decision aid. There are, however, several weaknesses in this methodology (*1*). The most significant is the lack of an unambiguous diagnostic gold standard. Shiomi et al. compared the fuzzy reasoning diagnosis to a scoring system which used the same five input variables on a three-point scale. Because the fuzzy reasoning system had more information than the three-point scale scoring system, it is not surprising that it had better accuracy. It would be more interesting to see comparisons to final clinical diagnosis, anatomical correlation between the two approaches, and, most importantly, to clinical decision making. One of the greatest challenges in the use of fuzzy reasoning lies in selecting proper membership functions. The authors state that they tried several different membership functions and fuzzy rules and found that the functions and rules provided in the article gave the best performance, but they do not describe this process. Methods for establishing these functions and rules are critical to allow the extension of this fuzzy reasoning system to include other variables and to allow other investigators to reproduce and extend this work.

CONCLUSION

Shiomi et al.'s study shows an interesting use of fuzzy reasoning that expands previous attempts of the use of fuzzy sets in this area (*11*). Further development of fuzzy reasoning, perhaps in combination with a neural network (*12*), may greatly expand the diagnostic utility of nuclear medicine testing.

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