The Fuzzy Medical Group in The Centre for Computational Intelligence,

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Abstract:

In this paper, five ongoing or completed research projects in medicine using fuzzy sets and logic are summarised. They are: a lightweight fuzzy process for diagnosis using fuzzy symptoms; prediction of pulmonary embolisms from linguistic descriptions of perfusion and ventilation scans; application of the fuzzy ART/MAP and MinMax/MAP neural network models to radiographic image classification; the development of a fuzzy expert system for the analysis of umbilical cord blood; modeling nursing intuition using type-2 fuzzy sets. These projects use a variety of fuzzy methods including clustering, simple set aggregation and type 2 inferencing to achieve their aims. The ongoing research projects reflect an interest in using Type 2 fuzzy sets for dealing with vagueness and linguistic knowledge which is commonly found in medical areas where perceptions rather than measurements are the norm.

Keywords: Diagnosis, FuzzyART, Clustering, Linguistic Variables, Type 2 fuzzy sets.

1. Introduction:

The aim of the group is to advance the state of the art of Computational Intelligence by the development of fundamental and applied methods in appropriate application domains such as Medicine. The philosophy of the group is to balance theory and application in a synergistic framework. In practice, the medical research is driven by medical need and theoretical advances in fuzzy sets and inferencing. All the research projects reviewed in this paper are the result of close collaboration with medical experts in local and national hospitals who are referenced where appropriate. Interested readers are directed to detailed references where appropriate. Please note that the research projects vary in their status from just started to just completed. This is indicated for each project.

2. A Lightweight Fuzzy Process to support Early Diagnosis of Confusable Diseases Using Causation and Time Relationships and Fuzzy Symptoms.

2.1 Application Domain:

In primary health care, a medical physician may have to deal with a small but important number of cases where relatively rare life threatening diseases (such as meningitis) can be confused with relatively common non-threatening diseases (such as the common cold) in their early stages. In such cases, it is dangerous to let a disease progress to a point where it can be unambiguously diagnosed or to wait for the results of detailed clinical tests. There are a number of non-exclusive approaches to decision support in these situations [1].

2.2 Problem:

The general problem with building decision support systems is data acquisition. For example, we may need to have exact frequency counts of well defined symptoms relating to all patients with well defined confirmed diseases. There are a number of problems with this on both a theoretical and practical basis. First, the actual occurrence or non-occurrence of a symptom is not in reality a crisp event. Patients suffer from a symptom to some degree (e.g. severe, mild, etc) over an ill-defined period (e.g. 'for about 2 days last week'). Secondly, the degree to which a patient suffers a disease is to some extent dependant on the patient's state of health and the cause(s) of the disease. Clearly, somehow a physician takes these into account when making a diagnosis using a hypothetico-deductive method.

We believe that, in these circumstances, a fuzzy approach may well be better suited to a decision support process than a crisp one. We therefore use a fuzzy representation of the possibilities of onset and demise of a symptom in time during the course of a disease.

2.3 Method:

The method takes each expected symptom for a particular disease from the knowledge base and, if it has been reported to have been observed over a period of time, determines first, a range of time for the stage of the disease given all observed symptoms so far, and second, a measure (M+) of the goodness of fit based on the 'center of area’ (COA) approach of the appropriate fuzzy sets. If an expected symptom has not been observed, a similar measure (M-) is computed using the COA of the appropriate fuzzy set with appropriate boundaries. An overall index of support (S) for the particular disease is computed using M+ and M-. M+ is analogous to the conditional probability of D given observation of a set of expected symptoms in a particular time. M- is analogous to the conditional probability of not having D given the absence of a set of expected symptoms in a particular time.

2.4 Results:

Test were made [2] showing how the support index values relate to two confusable diseases (influenza and scarlet fever) given a range of time intervals for symptom elicitation. These involved generating a database of about 90 different symptoms and how they are causally related to the example diseases. This information is readily available in linguistic form in many common references. We assumed for demonstration purposes that all symptoms were observed 3 days ago and are still present. We then assume observation of all the causally relevant symptoms for influenza only. As we entered information symptom by symptom we can see the effect on the support index. For the first 4 symptoms, scarlet fever has a larger index value that influenza reflecting the analogous prior probabilities from the time information in the sets. After this we see more evidence for influenza. When we vary the onset time information the same pattern is repeated except that as the duration of the symptoms is increased, the better the prediction of influenza as the supported disease.

We are now exploring the sensitivity of the method to fuzzy symptom information such as the strength of the symptom and its vague time definition. This involves using Type 2 fuzzy relations and defuzzification into a crisp symptom 'strength' for use in the method [3]. After developing the prototype, we expect to test the results in a primary care setting with a local general medical practitioner.

3. Prediction of pulmonary embolisms from linguistic descriptions of perfusion and ventilation scans.

This project is in collaboration with Mr. I Belton of the Dept. Medical Physics, Leicester Royal Infirmary, Leicester, U.K. It has recently started and uses a newly developed method of supervised learning of linguistic (Type 2) fuzzy information. Linguistic descriptions of perfusion and ventilation scans for pulmonary embolism patients are being used with this method to provide a prediction of estimates of likelihood of pulmonary embolisms for patients at risk. We intend to compare the results with existing methods using standard multi-layer feedforward networks [4]. Evaluation is planned over the next year when the appropriate parameters of the fuzzy sets will be optimised.

4. Application of the fuzzy ART/MAP and MinMax/MAP neural network models to radiographic image classification.

This project is in collaboration with Mr. M.Barnes of the Dept. of Sports Injuries, Leicester General Hospital, Leicester, U.K.

4.1 Application Domain:

There has been a marked increase in the number of people engaging in sport/exercise over the last fifteen years or so and a corresponding number of injuries presented in injury clinics. Clinicians have therefore built up significant expertise in recognizing and classifying these injuries and have accumulated evidence to support them such as bone scan radiographs (e.g. stage 3 scintograms). However, the incidence of exercise-induced lower leg pain at particular regional clinics is relatively low. Even at a specialist center, the incidence may be only 20 per year or so. Given that these cases can be classified into several main categories, it is by no means certain that every clinician will experience all classes of injury over a relatively long period of work. Furthermore, the less obvious classes are likely to be confused since they occur over a period of time where correlated features can be forgotten. The order and time of occurrence of presentation at the clinic is clearly important for these cases.

4.2 Problem:

There are distinct sources of uncertainty in images, which arise from various causes. Bone is a living tissue and as such is constantly being remodeled. Bone scanning is a technique, which produces an image of the bone, which indicates areas of abnormal bone turnover, which may indicate a pathological process. Unlike X-radiographs, scintograms do not reveal distinct clear images, which necessarily directly correspond with anatomical features. Thus the interpretation of the image is not trivial in the majority of cases. Our strategy is therefore to concentrate on capturing the human expertise, which copes with this variation, rather than try to normalize our automatic image processing methods using a small set of widely varying data.

For instance, the expert's judgement of the distinctiveness of a line on the image or whether a line is 'much longer' than it's width are important in assisting with the diagnosis. This subjective judgement is clearly a part of the expertise of the observer, which takes into account the differences between people, and yet this knowledge is not easily captured in numerical systems. We assume that this imprecision or uncertainty is well suited to fuzzy logic.

4.3 Method:

Knowledge acquisition is notoriously difficult for fuzzy systems since it is particularly difficult to determine membership functions. For this application the uncertain or imprecise nature of the knowledge needs to be captured as input to the clustering neural network. The knowledge acquisition was carried out by interview. The proposed solution is therefore to help clinicians by providing knowledge about the domain by a method, which allows them to see spatial relationships between temporally, collected images of shin injuries. It would not be possible with the paucity and imprecision of the data and the state of knowledge of the expert to provide an `automatic' classification, by, for example, applying standard methodologies for developing expert systems based on rules or back propagation neural networks. This research set out to address whether, with fuzzy neuro-clustering techniques some insights may be provided to the expert that they can use along with their experience and knowledge [5]. It is envisaged that this process is an essential first step in a methodology designed to improve knowledge acquisition for possible future classification systems.

The method is to perform classification analysis of exercise-induced lower leg pain by applying competitive neural network clustering and mapping techniques to type 1 and type 2 fuzzy descriptions of bone scan images of the tibia. The clusters are described and compared with each other and with the experts known classes that would be expected from medical findings. The discovered clusters provide training sets for supervised learning by an ARTMAP and similar neural network. These were used to classify the previously unclassified images and hence improve the classification process.

4.4 Results:

The group is particularly interested in the role of type-2 fuzzy sets in modeling perceptions and imprecision [6]. Type-2 fuzzy sets capture a higher level of imprecision than 'traditional' (type-1) fuzzy sets by allowing for fuzzy membership grades. Instead of a number in [0,1] the membership grade is a fuzzy set. This project used type-2 fuzzy sets to model the consultants' perceptions of the images to allow for submission to the various artificial neural network paradigms. Instead of translating words into single numbers in [0,1] they were translated into type-1 fuzzy sets which are membership grades of type-2 sets representing, for example, the location of any anomalies. The results show that in some instances the type-2 representation performed better than type-1 whilst in others the type-1 representation was a better predictor.

The overall conclusion [7] is that the use of the neural clustering methods has improved the classification process of the shin images despite the paucity of data and its inherent uncertainty. The method also provided a good model of how radiology expertise is obtained and used.

This project is completed.

5. The Development of a Fuzzy Expert System for the Analysis of Umbilical Cord Blood.

This project was carried out in association with Professor Ifeachor of the University of Plymouth.

5.1 Application Domain.

An assessment of neonatal outcome may be obtained from analysis of blood in the umbilical cord of an infant immediately after delivery. This can provide information on the health of the newborn infant and guide requirements for neonatal care, but there are problems with the technique.

5.2 Problem.

Samples frequently contain errors in one or more of the important parameters, preventing accurate interpretation and many clinical staff lack the expert knowledge required to interpret results. The development and validation of an expert system to overcome these difficulties is described.

5.3 Method.

The initial development utilized conventional 'crisp' logic within the rule base and this system was evaluated to commercial release [8]. This expert system validates the raw data, provides an interpretation of the results for clinicians and archives all the results, including the quality control and calibration data, for permanent storage.

5.4 Results.

Subsequent development went on to incorporate fuzzy logic into part of the expert system knowledge base, but tests of this preliminary fuzzy system [9] showed that it performed worse than the original crisp expert system. A tuning algorithm was then employed to modify the fuzzy model and this process resulted in improved performance to a level comparable to clinicians and superior to the crisp system. Finally, the entire knowledge base was converted to utilize fuzzy logic and this 'integrated' fuzzy expert system was validated against international expert opinion [10].

This project is completed.

6. Modeling Nursing Intuition using Type-2 Fuzzy Sets

This newly developed project is in collaboration with Sarah Lake, RGON, BN, of Nelson Hospital, Nelson Marlborough Health Services (Private Bag, Nelson.sarah.lake@nmhs.govt.nz).

6.1 Application Domain.

Nursing is grounded in the nursing knowledge base, which has been developed over time in praxis and defined within the oral tradition of nurses and the writing of nurse scholars. Nursing praxis reflects and is reflected by this knowledge, which is used by nurses to make decisions regarding patient care.

6.2 Problem.

Linguistic vagueness is the norm in this application domain and hence decision making is difficult and uncertain [11]. Traditional Type 1 fuzzy sets can be used for modeling uncertainty and then used for inferencing but estimation of the degree of membership is a major difficulty.

6.3 Method.

Our work suggests a method for modeling nurse decision making which is grounded in the nursing knowledge base and able to acknowledge not only the problem solving approach of the nursing process, but also goes some way to recognizing the complexity of context and degree of acuity of the nurse patient interaction [12]. It is our contention that current approaches have limitations and that fuzzy logic provides the ability to model the granularity of linguistic terms and, indeed, provides "Computing with Words”. Central to our approach is the use of type-2 fuzzy sets to model nursing concepts and the uncertainty expressed in linguistic terms in the nursing knowledge base. Any mathematical or (formal) logic approach to a problem requires either approximations to be made or to model the world as a black and white or true and not true. Such an approach makes little allowance for context and degree relevant to nursing. Patient need occurs to a degree in the context of the person's health or unwellness. For instance, nausea may occur in the context of pregnancy, post anaesthesia or terminal illness, to name but a few possible contexts. The degree of nursing intervention will depend not only on this context but also the degree of nausea experienced by the patient. 'Degrees of nausea' may include loss of appetite, nausea relieved by comfort care, nausea readily relieved by prescribed medication, or intransigent nausea. Intransigent nausea may require a range of prescribed intravenous anti-emetics as well as comfort cares before settling, while medication would be a last resort for the treatment of the nausea of pregnancy even if this were moderately severe.

A rationale to support the complexity of the process of assessment as a basis for nurse decision making can be modeled using developments in fuzzy logic. A framework of the matrix can be developed for an area of nursing practice, with the various degrees of acuity or level of patient need per domain ranked according to degree within the domain. Words ranking each degree of acuity would be chosen by nurses in this area of practice so that the words fit the common understanding of this praxis. The framework would reflect the decisions made by each nurse as to the degree to which each patient's need fit within each domain, and the degree of nursing intervention would be reflected accordingly. Fuzzy logic provides, by the use of fuzzy sets, the ability to represent vague or imprecise concepts. However it is our contention that type-2 fuzzy sets capture the uncertainty better and particular suit the domain of nursing. Type-2 fuzzy sets allow for the modeling of linguistic uncertainty since words can be used in a domain such that there is no requirement for precise membership functions as with type-1 fuzzy sets.

The project is in its early stages and there are no results to report yet.

7. Future Directions:

The use of fuzzy approaches has been successful in our work so far, which has addressed particularly difficult problems in the medical field involving classification and perception by experts of uncertain visual and linguistic information. We see future directions developing fundamental methods such as supervised learning of Type 2 (linguistic) fuzzy sets and exploring their applicability in the very rich and important area of medical diagnosis and analysis.

8. Resources:

http://www.cse.dmu.ac.uk/~rij/public_html1/irsg.html

9. References:

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