Modelling Nursing Intuition - a Non-Deterministic Approach

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Abstract

This abstract presents the initial results of exploring the notion of non-determinism in representing nursing intuition via type-2 fuzzy sets.

Keywords: nursing, type-2, non-determinism.

1 Introduction

Type-2 fuzzy logic [2,8,12] allows for us to capture and represent uncertainty in a different way to type-1 fuzzy logic. The growth of applications in type-2 fuzzy logic [1,3,4,7,11] highlights the opportunities offered. This work explores the role type-2 fuzzy sets in nursing.

The clinical reality of nursing requires nurses to make decisions arising from an ongoing holistic assessment of the patient need for nursing care, based on an extensive range of knowledge. Nurses concurrently assess patient need for nursing care in several domains of concern to nursing before deciding on where the primary focus of nursing attention should be directed. Holistic nursing assessment takes a number of domains of patient need into account, as well as the need for clinical intervention. Such nursing intuition is best represented by words and it’s our contention that type-2 fuzzy logic [8] is ideally placed to assist in this important application. Previous work [3,5] investigated the role of fuzzy logic in modeling the inherent uncertainty in the representation of nursing intuition. However this suffered from being a simplistic representation, which proved to be interesting but somewhat inconclusive. The work presented here extends that work by exploring a different approach to the role of type-2 fuzzy sets.

The framework for assessment of patients falls into five domains, which are discussed in the next section.

2 The Domains

Nursing is often carried out in conjunction with medical diagnosis and treatment. A primary focus of nursing concern is the physical/medical condition or diagnosis of the person. Therefore the initial domain of assessment is named ‘Physical/Medical Condition'. A domain named 'Complicating Factors', which may affect the initial condition, is then also considered and taken into account. The physical capability or 'Dependency' domain of the individual is always assessed. The patient's ability to understand and co-operate with suggested interventions and the support available to the person from their family and environment will also affect the amount and type of nursing intervention that will be provided. This domain has been summarised as the 'Psycho-Social' domain. The requirement for the more obvious array of nursing clinical interventions, as titrated to patient need and condition, are combined in the 'Clinical Intervention' domain. It is suggested that these five domains provide the context of the patient need for nursing care and intervention. These `top level' domains are clearly imprecise and subjective and are difficult, if not impossible to measure. The general nursing problem facing the nurse in clinical practice is to determine which intervention for any or all of the domains meets the patient need for care and should be done first.

Each domain is described according to five overlapping ordered qualitative categories of severity. These are provided in Table 1.

Table1: The Nursing Domains

Domain	Category
Physical/Medical condition	Stable Becoming stable Potentially unstable Unstable Critical
Complicating factors	Stable Becoming stable Potentially unstable Unstable Critical
Clinical intervention	Minor Technical necessary Complex Complex/risky Critical
Dependency	Independent Becoming independent Dependent Heavily dependent Totally dependent
Psycho-social needs	Coping well Medium (coping OK) Moderate (coping) High (not coping) Extremely high

The next section describes the problem and the approach taken.

3 Modelling Nursing Intuition and Type-2 Fuzzy Sets

For the particular context described in this work the nurse must decide by review of the five domains which imperative(s) to work with. The review effectively provides a summary of the patient's condition overall.

The problem is to take these symptoms and combine them into a category of the 'Overall Patient View' domain - see Table 2.

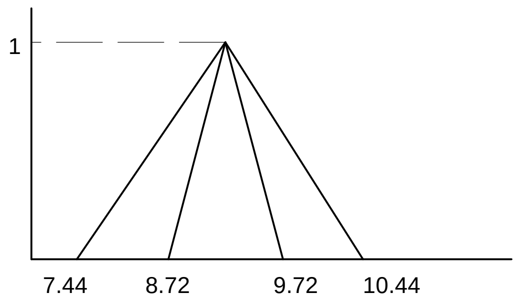
Table 2: Overall View Domain

Domain	Category
Overall patient view	Stable Becoming stable Potentially unstable Unstable Critically ill

All domains are given a continuous scale of 0 to 10 and each of the five categories, within the domain, is given a range of probable values (probable(lower) to probable(upper)) and a range of possible values (possible(lower) to possible(upper)). Where possible(lower) < probable(lower) < probable(upper) < possible(upper).

Figure 1 shows an example of this approach. In this example the category 'Critical' within the domain Physical/Medical condition has a possible (lower) value of 7.44, probable(lower)[8.72], probable(upper)[9.72] and possible(upper)[10.44].

Figure 1 : Triangular Secondary Membership function for the Critical category within the Physical/Medical Condition domain.



These values have been determined by knowledge acquisition from an expert nurse. The formation of the ranges allows the creation of triangular secondary membership functions, which may be termed the 'Footprints of Uncertainty' [8,9]. Clearly these ranges would best be learnt from data and this will be done in future work. This is non-trivial however and requires serious consideration.

These triangular FOUs can be represented by type-2 fuzzy sets as defined by Zadeh [12]. A type-2 fuzzy set, $\tilde{A}$, can be defined in the following way [9]:

$$\tilde{A} = \{((x,u), \mu_{\tilde{A}}(x,u)) \mid \forall x \in X, \forall u \in J_x \subseteq [0,1]\}$$

In other words, a type-2 fuzzy set is a fuzzy fuzzy set where the FOU can be defined as [9]:

$$FOU(\tilde{A}) = \bigcup_{x \in X} J_x$$

The secondary membership function is our third dimension and is a type-1 fuzzy set. For our purposes here we only consider interval valued fuzzy sets where the secondary membership function is an interval and has amplitude unity across that interval.

3.1 A typical patient

One of the patient's in our evaluation set has the profile shown in Table 3.

Table 3: Individual Profile

Domain	Category
Physical/Medical condition	Critical
Complicating factors	Unstable
Clinical intervention	Critical
Dependency	Totally dependent
Psycho-social needs	Moderate (coping)
Overall patient view	Critically ill

The nurse in evaluating the patient bases the final summary/overview on review of the five categories to see the overall picture. However, the input data into our system are numerical values. Since nurses use words to describe the patient and human observation can, by its very nature, be inconsistent for various reasons, e.g. different training methods or change in opinion over time, we have a problem in the 'fuzzification' of the system. The approach taken here is to view the fuzzification of categories from a stochastic point of view. In other words we can randomly select a number within the probable range and assess the overall view from this perspective. This is now particularly interesting since we have a non-deterministic solution thus replicating better, we believe, the reality.

3.2 Random numbers and 'Intervals of Uncertainty'

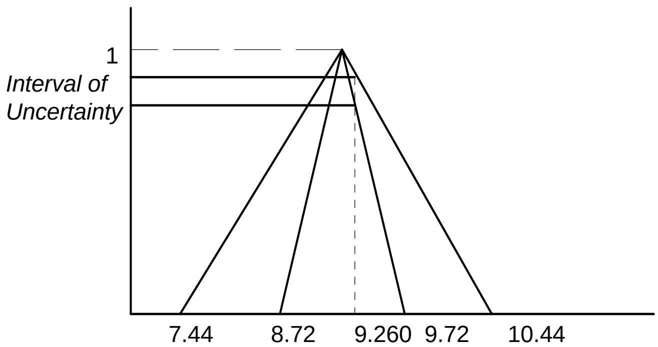
This patient is in the 'Critical' category of the Physical/Medical condition domain, the values for this category in this domain is shown in Figure 1. Our approach is to generate a random number in the range probable(lower) to probable(upper) i.e. between 8.72 and 9.72. The generated number is 9.560. Random numbers are generated for the other categories in exactly the same way; these are shown in Table 4.

Table 4 : Random numbers generated for input

Domain	Random number
Physical/Medical condition	9.560
Complicating factors	7.458
Clinical intervention	9.636
Dependency	9.021
Psycho-social needs	3.515

The five random numbers produce what we might call an 'Interval of Uncertainty' within each domain. Figure 2 shows how the random number for the critical category within the Physical/Medical condition domain is introduced into the system and how the 'Interval of Uncertainty' is generated.

Figure 2 : Illustration of an 'Interval of Uncertainty'



Since categories overlap it is possible for a random number to belong to more than one category and hence for more than one 'Interval of Uncertainty' to exist within a domain. Thus, within each domain, we combine the interval fuzzy sets using 'meet'. This provides an interval valued set that, in some way, represents the domain under consideration. The research reported here uses both the minimum t-norm and product t-norm [8]. Once this has been done for each domain to arrive at an overall result we need to combine these intervals. To do this we use the 'join' [8] with a max t-conorm. The results for the given patient are shown in Table 5.

Table 5 : Interval function limits

	Lower limit	Upper limit
Using 'minimum meet'	0.143	0.468
Using 'product meet'	0.111	0.310

There are some interesting issues still to be investigated here. Firstly, these intervals tell us nothing about the outcome.

Secondly, for the same set of random numbers we produce non-overlapping intervals.

As an alternative approach, we have looked at, for each patient, calculating the mean of the random numbers and entering this into the 'Overall patient view' domain. The mean of the five random numbers for this example is 7.838. This lies exclusively in the 'Unstable' category of the 'Overall patient view' domain. The limits of the interval function produced are shown in Table 6.

Table 6: Results using mean random numbers

Lower limit	Upper limit
0.676	0.772

The non-deterministic approach to fuzzification allows more flexibility for better representation of the real decision making process. It also allows us to run series of experiments to evaluate the effectiveness of our type-2 representation. The next section explores some of these initial results

3.3 Some randomized experiments

For the same patient we carried out the analysis a further three times. The results are summarised in Table 7.

Table 7 : Interval function limits for each run of the experiment.

		Lower limit	Upper limit
Run 1	Minimum meet	0.247	0.546
	Product meet	0.147	0.342
Run 2	Minimum meet	0.254	0.537
	Product meet	0.160	0.473
Run 3	Minimum meet	0.239	0.472
	Product meet	0.176	0.354

Again we use the mean of the five random numbers for the five domains of each run and enter it into the 'Overall patient view' domain. Table 8 shows the limits of the interval function and the categories where the mean lies in the 'Overall patient view' domain.

Table 8 : Results using the mean of the random numbers for each run.

	Lower limit	Upper limit	'Overall patient view' categories
Run 1	0.652	0.755	Unstable
Run 2	0.471	0.628	Unstable
	0.000	0.155	Critically ill
Run 3	0.867	0.906	Unstable

In most of the experiments we have carried out the mean of the five random numbers usually lies in the 'Overall patient view' category given by the nurse. However, because the categories overlap multiple categories are not unusual.

For the example given in this paper, the patient being considered has an 'Overall patient view' category of 'Critically ill'. Table 8 shows that the mean for Run 2 lays in both the 'Unstable' and 'Critically ill' categories but for Runs 1 and 3 the means are exclusively in the 'Unstable' category.

Clearly, there are some interesting issues still to be investigated here. Further work will explore what the relations are between the interval(s) produced from the individual profile and interval(s) produced from the ‘Overall patient view’. We need to find an efficient and effective way of comparing the results of our simulations with the expected results and indeed see an obvious need for a learning mechanism for the type-2 fuzzy sets.

4. Conclusion

This approach clearly presents a step forward in non-deterministic reasoning in the clinical practice application domain. In this paper we have been able to provide a flavour of our methodology. Future work will consider more patients, present an approach for analyzing the outcome of the methodology and will present new ideas on defuzzification for such a problem.

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