FMTS: A fuzzy implementation of the Manchester triage system

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FMTS: A Fuzzy Implementation of the Manchester Triage System

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***Abstract*—Manchester Triage System is an algorithmic standard designed to aid the triage nurse in choosing an appropriate triage category using a five-point scale. Many of the terms used in Manchester Triage algorithm to describe patients' symptoms and their urgency levels are imprecise and overlap making the system a good candidate for fuzzy modeling. The paper develops a dynamic fuzzy triage system based on the Manchester triage algorithm. The system severs as a decision aid for the triage nurse while allowing medical experts to configure the meaning of the linguistic terms using a fuzzy mouse.**

I. Introduction

The Manchester Triage System (MTS) [1] is a widely used standard in the UK and Europe for prioritizing patients in the emergency room. The system consists of around 50 flowcharts with standard definitions designed to categorize patients arriving to an emergency room based on their level of urgency. Figure 1 shows an example of one such flowchart designed to evaluate the treatment urgency for the shortness of breath in children.

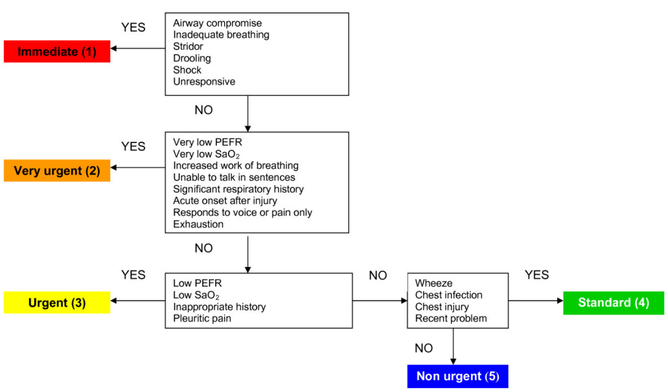

Fig. 1. An example of an MTS flowchart for evaluation of the urgency of the shortness of breath in children

Unlike the conventional doctor visit where patients are treated by appointment or on a first-come-first-served basis, patients admitting to the emergency room must be handled on the basis of the urgency of their situation. A likely scenario is one where hundreds of patients may present themselves to the emergency room, many arriving on or around the same time, and many of them will have symptoms that are difficult to assess in terms of level of urgency and priority. The evaluation of these situations is typically performed by a triage nurse who collects patient information and relies on her memory of guidelines and subjective assessment to assign an urgency level to patients. For a triage nurse with 50 flowcharts in her hand, trying to correctly prioritize a patient is a clumsy process. The evaluation is typically performed by a triage nurse who collects patient information and relies on her memory of guidelines and subjective assessment to assign an urgency level to patients. For a triage nurse with 50 flowcharts in her hand, trying to correctly prioritize a patient is a clumsy process.

MTS flowcharts are full of imprecise linguistic terms such as very low PEFR, exhaustion, significant respiratory history, urgent, etc. this might result in two nurses coming to different conclusions about the urgency of a patient's condition even if the same flowcharts are being used. What does it mean for PEFR to be very low? What about the output? What is the difference between very urgent and urgent? What does the categorization of a patient mean for her waiting time to be treated? If two children are in triage for shortness of breath and one has what would be considered very low oxygenation (SaO2) and the other has acute onset after injury, which should be seen first? Which can afford to wait longer than the other? These situations are both considered very urgent by the flowchart. A crisp output is needed if we want to distinguish precisely between these two types of patients. All this suggests that there is a need for an objective triage system that can correctly model the meaning of imprecise terms in the MTS and assign an appropriate waiting time to patients. Hence, an objective triage system is needed that can correctly model the meaning of imprecise terms in the MTS and assign an appropriate waiting time to patients.

This paper develops a Fuzzy Manchester Triage System (FMTS). FMTS is a dynamic fuzzy inference system which implements the flowcharts designed by the Manchester Triage Group. FMTS provides two user interfaces: one is a decision aid system for the ER nurses to properly categorize patients based on their symptoms, and the other one is a knowledge acquisition component used by the medical experts to configure the meaning of linguistic terms and maintain the fuzzy rules. The concept of Z-mouse and fuzzy mark [2], [3] is used to provide an easy-to-use visual means for fuzzy data entry in the knowledge acquisition component.

II. Related Work

Current literature on triage decision aid systems can be classified into two main categories: knowledgebase systems and data driven systems. The knowledgebase systems are built based on the rules provided by the medical professionals while data driven systems use machine learning approaches to train and build a classification model based on patient data. The machine learning approaches to triage support systems [4], [5] are typically more tolerant to noise and can learn a complex model from high dimensional data samples; however, these models do not follow a standard approach to the prioritization of patients. Furthermore, it is difficult to choose a method with an appropriate hypothesis space which contains the solution to the problem while ensuring reliable generalization from patient data [6]. In addition, an empirical study [7] shows that the machine learning models do not generally show any statistically significant advantage over hand-crafted expert systems when it comes to classification problems.

A few number of knowledgebase systems have been developed to support triage decision-making. iTriage [8] is an expert system that implements the Australian Triage Standard. iTriage benefits from an advanced user infterface and produces robust decision for urgent scenarios. However, the system accepts a limited number of input variables and uses crisp rules to convert the linguistic terms such as mild pain into a numeric value. Other knowledgebase triage support systems [9], [10] are very narrow in their scope or suffer from a low accuracy level.

III. Description of FMTS

FMTS, to our knowledge, is the first dynamic fuzzy implementation of the Manchester Triage Standard. Figure 2 shows the overall view of the FMTS. The nurse triage component is used to choose among 49 different reasons that a patient presents herself to the emergency room. Once a particular reason is selected then all the symptoms related to that reason appear and the nurse enters a linguistic value for each symptom. These values are then translated to numeric inputs and are fed into the fuzzy inference system to produce the urgency of the situation, another fuzzy term that then translates to the amount of time a patient can safely wait to be treated.

In sum, the Fuzzy Inference system in FMTS consists of 35 input linguistic variables for various symptoms, one output linguistic variable for the level of urgency, and 980 fuzzy rules to map a patients symptoms to her treatment urgency.

The knowledge acquisition component in FMTS allows medical experts to modify the meaning of fuzzy terms and hence makes the system more dynamic. An expert can choose among 35 unique linguistic variables related to a patient's symptoms and then modify the membership functions representing the fuzzy terms related to that variable.

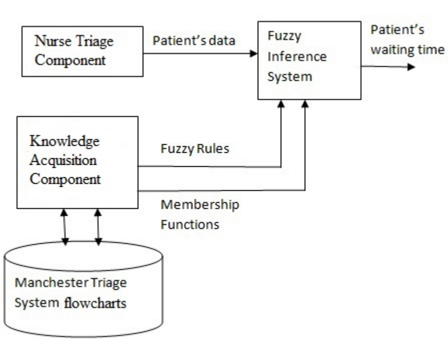

Fig. 2. overall architecture of the FMTS system

A. The Nurse Triage Component

The first item of business when a patient enters an emergency room is to triage the patient. In other words, a triage nurse must first determine what brought the patient to the emergency room in the first place and then, based on symptoms related to their reason, determine the patients level of urgency. The Nurse Triage Component of FMTS provides a menu of common reasons a patient arrives at an emergency room. Each option provides a GUI to receive input from the nurse. Input received is for a description of the patients symptoms for a particular reason for presenting. Figure 3 shows an example of the nurse triage GUI for symptoms related to head injury.

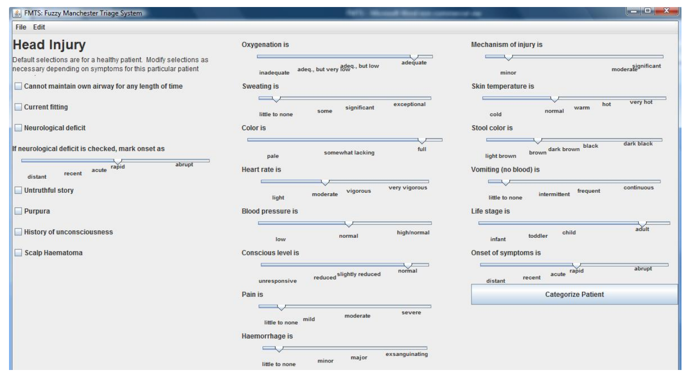

Fig. 3. A snapshot of the nurse decision aid GUI where chest pain is selected as the reason for arriving at the emergency room

A Symptoms can be either crisp or fuzzy. A crisp symptom (such as: can a patient maintain her airway for any length of time?) is entered via a checkbox while fuzz input (such as: what is the patients' heart rate light, moderate, vigourous, or somewhere in between?) are entered using sliders. The sliders contain descriptions of linguistic terms that can be used to convey a verbal description of what a patient is experiencing. A nurse may move a slider to a position he feels appropriately portrays each symptom. Sliders default to positions typical of a healthy patient, allowing the nurse to only address those sliders that apply while leaving the rest. Many of the labels on the slider match the linguistic values provided by MTS flowcharts and will be positioned according to the placement provided by the domain expert. The labels provide a spectrum of meaning for each variable that generally rank in intensity, from the relatively benign to the more pronounced. As shown int figure 3, the labels are positioned to allow for some overlap amongst the terms. the fuzzy input variables used in each reason to present to the emergency room, along with the fuzzy output variable situation that is used to describe the level of urgency of the situation at hand.

Table I presents the input fuzz variables and their related linguistic terms used in each reason to present to the emergency room. The last row shows the fuzzy output variable situation that is used to describe the level of urgency of the situation at hand. Once the nurse is satisfied that she has used the nurse triage GUI to appropriately describe the patients symptoms, FMTS takes the crisp inputs provided by the sliders and check boxes and maps them to membership functions that represent the fuzzy values for the fuzzy variables in question. The degree of membership determined decides what rules are

TABLE I. THE LINGUISTIC VARIABLES IN FMTS AND THEIR RELATED FUZZY TERMS

Fuzzy Variable	Linguistic Terms
oxygenation	inadequate, adeq. but very low, adeq. but low, adequate
sweating	little to none, some, significant, exceptional
color	pale, somewhat lacking, full
heart rate	light, moderate, vigorous, very vigorous
blood pressure	low, normal, high/normal
conscious level	un-responsive, reduced, slightly reduced, normal
pain	little to none, mild, moderate, severe
vaginal bleeding	little to none, light, heavy
pregnancy	impossible, slightly possible, unsure, early stage, late stage
skin temperature	cold, normal, warm, hot, very hot
onset of symptoms	distant, recent, acute, rapid, abrupt
stool color	light brown, brow, dark brown, black, dark black
	little to no pink, pink, dark pink, red, dark red
vomiting (no blood)	little to none, intermittent , frequent, continuous
crying	little to none. intermittent, continuous, in-consolable
joint temperature	normal, warm, hot, very hot
life stage	infant, toddler, child, adult
itch	little to none, mild, moderate, severe
history of allergy	little to none, some, significant
rash or blistering	little to none, minimal, widespread
haemorrhage	minor,major, exsanguine
pefr	very low, low, normal
deformity	little to none, moderate, significant
mechanism of injury	minor, moderate, significant
history of respiratory	little to none,some, significant
risk of harm to others	low, moderate, high
risk of harm to self	low, moderate, high
history of psychiatric	little to none,some, significant
lethality	little to none,moderate, high
history of cardiac	little to none, some, significant
discharge or blistering	little to none, minimal, widespread
vision loss	little to none,some,complete
history of gi bleeding	little to none, some, significant
history of haematology	little to none, some, significant
ability to pass urine	normal, difficult, little to none
situation	immediate, very urgent, urgent standard, non-urgent

TABLE II. THE FUZZY RULES IN FMTS NURSE TRIAGE COMPONENT

Rule 1:	IF airway IS NOT maintained THEN situation IS immediate WITH 1.0
Rule 2:	IF oxygenation IS inadequate THEN situation IS immediate WITH 1.0
Rule 3:	IF (sweating IS significant OR sweating IS exceptional) AND (color IS pale) AND (heart rate IS vigorous OR heart rate IS very vigorous) AND (blood pressure IS low) AND (conscious level IS reduced OR conscious level IS unresponsive) THEN situation IS immediate WITH 1.0
Rule4:	IF haemorrhage IS exsanguinating THEN situation IS immediate WITH 1.0
Rule 5:	IF pain IS severe THEN situation IS very urgent WITH 0.8
Rule 6:	IF mechanism of injury IS significant THEN situation IS very urgent WITH 0.8
Rule 7:	IF shortness of breath IS present AND (onset IS acute OR onset IS rapid OR onset IS abrupt) THEN situation IS very urgent WITH 0.8
Rule 8:	IF neurological deficit IS present AND (onset2 IS abrupt OR onset2 IS rapid OR onset2 IS acute) THEN situation IS very urgent WITH 0.8
Rule 9:	IF (conscious level IS slightly reduced OR conscious level IS reduced OR conscious level IS unresponsive) THEN situation IS very urgent WITH 0.8
Rule 10:	IF haemorrhage IS uncontrollable major THEN situation IS very urgent WITH 0.8
Rule 11:	IF untruthful story IS present THEN situation IS urgent WITH 0.6
Rule 12:	IF neurological deficit IS present AND onset2 IS recent THEN situation IS urgent WITH 0.6
Rule 13:	IF haemorrhage IS uncontrollable minor THEN situation IS urgent WITH 0.6
Rule 14:	IF history of unconsciousness IS present THEN situation IS urgent WITH 0.6
Rule 15:	IF pain IS moderate THEN situation IS urgent WITH 0.6
Rule 16:	IF swelling IS present THEN situation IS standard WITH 0.4
Rule 17:	IF deformity IS moderate OR deformity IS significant THEN situation IS standard WITH 0.4
Rule 18:	IF pain IS mild THEN situation IS standard WITH 0.4
Rule 19:	IF onset of symptoms IS recent THEN situation IS standard WITH 0.4

fired and to what extent. The rules come directly from the flowcharts. The membership functions are determined by an expert with the aid of the knowledge acquisition component.

Table II is a set of fuzzy rules designed to properly categorized the patients that complain from "assault". Other reasons to present to the emergency room have similar rules that are unique to those reasons. Each level of urgency carries its own weight, with more urgent categories carrying the greater weights. The greatest level of urgency, immediate, carries the greatest weight, 1.0. Lower levels of urgency carry gradually lower weights ranging from 0.8 to 0.4. Assigning weights to fuzzy rules helps ensure that the rules indicating prompt life-saving measures be taken precedence over rules that indicate less urgent measures. The fuzzy rules tell the system what conditions necessitate certain levels of urgency (e.g., very urgent). Rules are fired to varying degrees, depending on to what degree a patient exhibits particular symptoms, and therefore the patient can qualify for different levels of urgency to varying degrees. That urgency level for which the patient most qualifies is examined for where it is at its maximum, and the right-most maximum value is converted to the maximum amount of time a patient can safely wait to be treated by a physician.

B. The Knowledge Acquisition Component

As mentioned previously, most of the linguistic variables and their values come directly from the flowcharts provided by the Manchester Triage Group. However, the mathematical meaning of those fuzzy values was not provided and so a knowledge acquisition component is indicated. This component seeks to obtain an experts knowledge of the meanings of those values in such a way that hides the technical details of their membership functions. This was achieved by presenting the expert with a GUI that allows her to position circles, as well as make changes to their diameter, in relation to other circles that are used to represent related linguistic values. These circles are called fmarks or fuzzy marks [2], [3] and are illustrated in figure 4.

Fmarks facilitate knowledge acquisition process and provide a visual means for fuzzy data entry. Modifying fmarks in this fashion allows the expert to configure both the type (either trapezoidal or triangular) and shape of each membership function. The black center of each circle represents that range of values where the membership function is at its maximum and can be thought of as the top side of a trapezoid. Clearly, if this black center is not present (i.e., has a diameter of zero), then the top of the trapezoid has no width and thus the shape becomes a triangle. The yellow portion of each circle represents that range of values where membership is only partial. Its width can be thought of as the base of the trapezoid. The sides of the trapezoid (triangle) adjust according to the selected diameters of both circles.

An expert can adjust the positioning of fmarks by moving the sliders below them. As the slider moves left and right, the corresponding circles follow. This allows the expert to define descriptors in relation to each other. For example, if the expert considers the fuzzy terms moderate and significant to be close in definition, then he can place their fmarks close to each other. Similarly, the expert can adjust the diameters of each circle by moving the sliders to the right of the fmark. Overlap between the membership functions can be achieved by making sure that the circles overlap, much like they do in figure 4.

When the changes to the membership functions are complete, the FMTS Nurse Triage component is updated and the labels on the sliders for collecting the symptoms (figure 3) adjust to coincide with the adjustments made in the knowledge acquisition component. For instance, if the expert moves the fmarks of two fuzzy values close together in the knowledge acquisition GUI, then the corresponding labels in the FMTS Nurse Triage GUI will be close together.

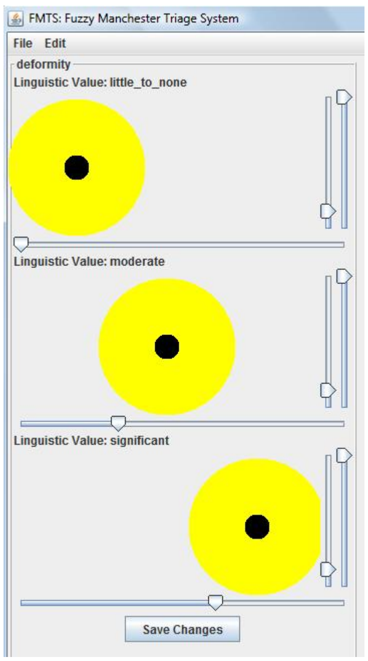

Fig. 4. the knowledge acquisition component for modifying the meaning of the linguistic terms related to the "deformity"

IV. Evaluation

FMTS was evaluated based on the practice cases designed for emergency nurses by the Agency for Healthcare Research and Quality (AHRQ) [11]. The expected outcomes (those generated by an expert) were produced using the philosophy of the Emergency Severity Index (ESI), another 5-category system like the one produced by the Manchester Triage Group, but with slightly different ideas about how to assess a particular situation.

Since FMTS is a fuzzy system, patients that get triaged can possibly belong to multiple categories at once because they partly qualify for more than one based on their symptoms. We consider FMTS to correctly triage someone if the expected result matches at least one of the results the system produces. So if the expected result is urgent and FMTS indicates the situation is somewhere between urgent and very urgent, then we say FMTS accurately predicted the triage category. We

TABLE III. The confusion matrix of test cases: Expected= triage category provided by domain expert, Actual= triage category determined by FMTS

Expected/Actual	1-Immediate	2-Very Urgent	3-Urgent	4-Standard	5-Non Urgent
1-Immediate	9	6	0	0	0
2-Very Urgent	0	19	5	1	0
3-Urgent	0	5	16	4	0
4-Standard	0	0	4	11	1
5-non-urgent	0	1	0	2	9

arrive at which category is indicated by comparing the output of maximum safe waiting time to be seen produced by FMTS to the ranges acceptable for each category. Out of 93 relevant practice cases, FMTS put 64 in an urgency category that exactly matched that of the expert while 27 were only one category away from the expert assessment and only 2 cases were off by more than one category. Table III is the confusion matrix comparing the expected and actual results obtained for these test cases.

V. Summary and Future Work

This paper presented a fuzzy implementation of the Manchester triage system. Compared to similar knowledgebase triage systems [8], [9] FMTS benefits from:

- a fuzzy modeling of patient's symptoms.
- a much wider scope. For instance, iTriage [8] considers only 8 inputs for modeling patients conditions while FMTS is more comprehensive and includes 50 reasons for arriving at an emergency center and about 35 input linguistic variables for modeling symptoms related to each reason.
- an easy-to-use knowledge acquisition component which makes the system dynamic and configurable by the domain expert.

For future work, we are planing to increase the accuracy of FMTS by combining expert's rule with those derived from patient's data using neuro-fuzzy systems. In addition, the current system allows expert to only configure the meaning of linguistic values. The knowledge acquisition component of FMTS should be extended to allow for fuzzy rule configuration.

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