A Multi-State Fuzzy Categorical Model for Military and Civilian Traumatic Brain Injury

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Abstract

Many traumatic brain injury (TBI) cases go undetected and untreated indefinitely during and post deployment, putting soldiers at risk and linked with significant long-term psychological disorders, disabilities, and economic burdens. Existence and severity are assessed via a range of initial subjective screenings in the field and subsequent cognitive and neurological assessments as a soldier returns to base, is discharged, and returns home. We describe a longitudinal fuzzy prediction model to categorize soldiers into one of four health states – no, mild, moderate, or severe TBI – using all assessment data available at any point in time and discuss preliminary performance results.

Keywords
TBI, military, healthcare, screening tests

1. Introduction

Traumatic brain injury (TBI), defined as any non-penetrating or penetrating structural injury or physiological disruption due to an external force, is a major military and public health problem and a common cause of civilian death and disability in the United States. Falls, impacts, motor vehicle accidents, and assaults are the most common causes of civilian TBI [1]. Each year, at least 1.4 million people sustain a TBI of which roughly 50,000 die, 235,000 are hospitalized, and 1.1 million are treated and released from an emergency department [2]. Military personnel and others working in combat zones also are at particular risk from explosions, rocket-propelled grenades, improvised explosive devices, and land mines, with TBI often occurring simultaneously with other more obvious life threatening injuries and thus overlooked [3].

TBI has been identified as the "signature injury" among U.S. troops serving in the wars in Afghanistan and Iraq, accounting for a larger proportion of casualties than it has in other recent U.S. wars. Because advances in protective equipment and battlefield care have reduced the incidence of penetrating head injuries and death, incidence of closed-head TBI has increased significantly. Some estimates of military TBI are as high as 22% [6]. As of February 2008, a total of 5,926 soldiers suffering from TBIs were reported by the Defense and Veterans Brain Injury Center (DVBIC), with 76% sustaining their injury while in the Army, 18% while in the Marines, 2% while in the Navy, and 2% while in the Air Force [5]. Severity of a TBI can be mild, moderate, or severe, depending on the extent of the damage to the brain with possible symptoms indicating increasing severity including headaches, confusion, dizziness, blurred vision, fatigue or lethargy, temporary loss of consciousness, change in sleep patterns, behavioral or mood changes, memory or concentration problems, repeated vomiting or nausea, convulsions or seizures, slurred speech, loss of coordination, and increased confusion, restlessness, or agitation [4].

Most diagnosed TBIs (86%) are categorized as mild, with moderate (7%), severe (4%), or penetrating wounds (3%) being far less common. The determination of moderate, severe, and penetrating TBIs is relatively straight forward because of the more visible nature of the injury, but mild TBIs are much more difficult to identify. Patients may not immediately experience, recognize, or seek care for mild TBI injuries. They, their caregivers, or screening mechanisms may attribute TBI symptoms to other diseases [5]. In combat zones, TBI often occurs simultaneously with more obviously life-threatening injuries; therefore, cases may go unrecognized, potentially putting the individuals or their units at risk. Additionally, when TBI occurs with no outward signs of trauma, service members might not seek medical treatment [6]. Delays in treatment can compromise recovery or result in significant cognitive, physical and/or psychological impairment, and therefore soldiers exposed to blasts should be screened for TBI immediately following the event to minimize medical complications [3].

Existence and severity of TBI are assessed in several ways: subjective assessments, external signs, physical experiences, neurologic assessments, and clinical assessments. In the military, testing typically follows a process of screening, identification, evaluation/confirmation, and stratification by severity. Jackson et al [8] describe screening mechanisms to detect TBI incidence among veterans of Operations Enduring and Iraqi Freedom. TBI is a significant enough military problem that Côté et al [14] developed a mixed integer programming model for locating treatment units in the Department of Veterans Affairs (VA). This optimization model assigns TBI treatment units to existing VA medical centers while minimizing the sum of patient treatment costs, patient lodging and travel costs, and the penalty costs associated with foregone treatment revenue and excess capacity utilization.

While ideally all TBI would be detected soon after the time of injury, initial tests tend to be less accurate than more thorough and expensive post-deployment tests. In practice, more than one method can be used for diagnosis to assure reliability and accuracy. Guler et al [7] developed a diagnostic system for determining the severity of civilian TBI by combining information from Glasgow Coma Scores (GCS) and electroencephalogram (EEG) results using fuzzy logic, a computational paradigm for processing information in a way that resembles human reasoning in the presence of uncertainty [11]. In this case, fuzzy inferences are obtained from GCS and EEG trauma score data which then are used to produce a trauma severity degree (Q) and final diagnoses for each patient. Fuzzy logic also has been successfully used in other healthcare applications for similar categorization purposes. For example, Veryha et al [12] describe a framework for implementing fuzzy classifications in primary dental care services and Dalalah et al [13] conducted a multicriteria decision analysis using fuzzy reasoning for remote health service delivery between a healthcare provider and patients. According to Khan et al [15], hybrid fuzzy decision tree classification for cancer prognosis is more robust and balanced than independently applied "crisp" classification, and has the potential to adapt for significant performance enhancement.

Since mild TBI symptoms are difficult to identify immediately, mild cases may not be diagnosed using one-time-screening techniques. We extend the above ideas to develop a more comprehensive procedure by sequentially applying fuzzy inference longitudinally to a series of screening results as they become available. Each single screening test i returns a crisp trauma severity degree (Q_i) between 0 and 100 similar to above. In order to get a final determination, each screening test result then is fed to a second fuzzy inference system in order to combine the information from each test, where the final determination might change continuously.

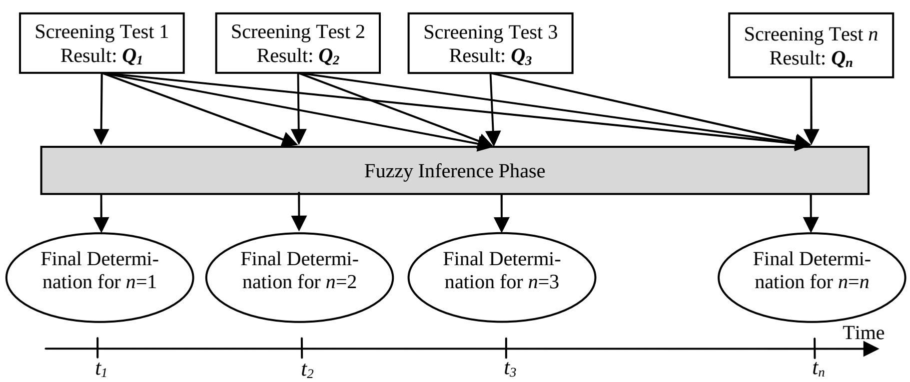

Figure 1: Longitudinal fuzzy TBI classification model

2. General Fuzzy Modeling Process

Fuzzy logic emulates the ability of humans to categorize things by comparing them with prototypical (characteristic) examples of the categories rather than evaluating whether they satisfy some unambiguous definition [9]. A fuzzy variable (also called a linguistic variable) is characterized by its name tag, a set of fuzzy values (also known as linguistic values or labels), and the membership function of these labels; these latter functions assign a membership value, $\mu_{\text{Label}}(u)$, to a given real value u (R), within some predefined range (known as the universe of discourse). Two basic operations, "*and*" and "*or*", are defined in fuzzy logic as [10]:

Definition 1: $\mu_{A \text{ and } B}(u) = \mu_A(u) \wedge \mu_B(u) = \min\{\mu_A(u), \mu_B(u)\}$

and

Definition 2: $\mu_{A \text{ or } B}(u) = \mu_A(u) \vee \mu_B(u) = \max\{\mu_A(u), \mu_B(u)\}$, where here *A* and *B* are fuzzy variables. Using such fuzzy operators, fuzzy variables can be combined to form fuzzy-logic expressions.

The general fuzzy logic algorithm consists of three activities: *fuzzification*, *fuzzy inference*, and *defuzzification*, as illustrated in Figure 1. Fuzzification is the process of making a crisp numeric quantity fuzzy [11] by mapping precise data inputs onto fuzzy membership functions. Typically, conventional trapezoid shapes such as those shown in Figure 2 are used to calculate fuzzy membership functions or degrees of membership for each category as

$$\mu(x_i) = \begin{cases} \frac{x_i - a}{b-a}, & a \le x_i \le b \\ 1, & b < x_i < c \\ \frac{d - x_i}{d-c}, & c \le x_i \le d \\ 0, & \text{otherwise} \end{cases}, \tag{1}$$

where *a*, *b*, *c*, and *d* are the defining parameters of each membership function.

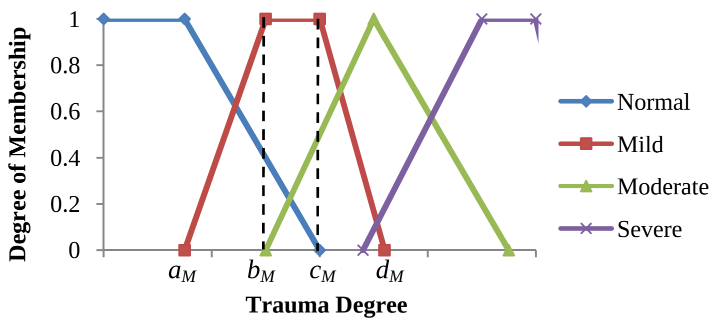

Figure 2: Fuzzy membership functions for the trauma severity degrees (coordinates shown for one test result)

In the second step, fuzzy inference is the process of obtaining a fuzzy output using a rule base that combines several inputs (here several screening tests), i.e., the results of the above fuzzification linguistic inputs. The rules in the rule base define the connection between input and output fuzzy variables. A fuzzy inference rule has the form *if antecedent then consequent*, where *antecedent* is a fuzzy-logic expression composed of one or more simple fuzzy expressions connected by fuzzy operators, and *consequent* is an expression that assigns fuzzy values to the output variables [10]. Relationships obtained from the rule base are interpreted using *and* operator. The outputs obtained from the rule base are interpreted using *or* operators [7].

Finally, defuzzification is the conversion of these fuzzy quantities to a crisp values. The output of a fuzzy process can be the logical union of two or more fuzzy membership functions defined on the universe of discourse of the output variable. Several methods exist for defuzzifying fuzzy membership functions, including the max-membership, center of gravity (COG), weighted average (WA), mean-of-maxima membership (MOM), center of sums (COS), center of largest (COL) area, and first or last of maxima (FOM or LOM) methods [11]. The present study compared the results of four of these methods - COG, MOM, FOM, and LOM. By example, maxima methods identify values with maximum membership, whereas in the COG method, a popular approach, the center of gravity of the area under the membership functions is calculated as the moment

$$z^* = \frac{\int \mu_{\underline{C}}(z) \cdot z \, dz}{\int \mu_{\underline{C}}(z) \, dz}, \tag{2}$$

where $\underline{C}$ is the union of the membership functions.

3. Longitudinal TBI Classification Model

3.1 The Proposed Model

Applying a fuzzy diagnostic system sequentially *n* times (i.e., to *n* screening test results) eventually will produce *n* trauma severity degree values (Q_1, Q_2, …, Q_n) for each patient, which become the inputs to the fuzzification logic shown in Figure 1. Four fuzzy sets – normal (no TBI), mild, moderate, and severe – are formed for these values using the four trapezoid membership functions shown in Figure 2 (which will be different for each screening test, resulting in 4*n* membership functions). Note that the limits of each membership function (a_i, b_i, c_i, and d_i for fuzzy set i = N(ormal), M(ild), Mo(derate), and S(evere)) typically might be determined by experts or via an optimization tuning routine, such as discussed below. Membership degrees for each category (i.e., for each of the four trauma severities) are computed from Equation (1) above.

For the fuzzy inference step, a rule base such as that shown in Table 1 is used, consisting of four linguistic outputs – normal, mild, moderate, and severe – the same as membership functions. Table 1 illustrates a rule base for the case with two screening results (n = 2), which again would be formed by experts or via some type of optimization logic. As seen, after the second screening there are 4^2 = 16 rules. To illustrate interpretation of this rule base, if the output of screening test 1 is 'mild' (column 2) and the output of screening test 2 is 'moderate' (row 3), then the output of the fuzzy inference process is 'moderate' (shown in blue font). According to the rule base and using min-max operators, the fuzzy outputs of the inference process are obtained and represented by $\mu_i^s(x_i)$ which means that, according to the result of screening test s, a patient belongs to fuzzy set i with a membership degree of μ_i^s evaluated at x_i. These fuzzy values then are converted into crisp values using the defuzzification methods mentioned above.

Table 1: Example of a rule base for n = 2 case

The output of the inference		Output of screening test 1			
		Normal	**Mild**	**Moderate**	**Severe**
Output of screening test 2	**Normal**	Normal	Mild	Mild	Mild
	Mild	Mild	Mild	Moderate	Moderate
	Moderate	Moderate	**Moderate**	Moderate	Severe
	Severe	Moderate	Severe	Severe	Severe

3.2 Example: n = 4 Screening Tests

To illustrate this process, consider the n = 4 case with four screening tests where the trauma severity degrees obtained from these screening tests for a given patient are $Q_1 = 45, Q_2 = 56, Q_3 = 63,$ and $Q_4 = 20$ and where the parameters of each membership function are: $a_N = b_N = 0, c_N = 15, d_N = 40, a_M = 15, b_M = 30, c_M = 40, d_M = 50$, $a_{Mo} = 30$, $b_{Mo} = c_{Mo} = 50$, $d_{Mo} = 75, a_S = 50, b_S = 70, c_S = 80$. (For simplicity, we here assume the membership functions have the same parameters for all 4 tests, although in reality they likely would be different.) According to these fuzzy membership functions and using Equation (1), the membership degrees for each TBI category are

$$\mu_M^1(45) = \frac{d_m - Q_1}{d_m - c_m} = \frac{50-45}{50-40} = 0.5 \tag{3}$$

and similarly $\mu_{Mo}^1(45) = 0.75, \mu_{Mo}^2(56) = 0.76$ and $\mu_S^2(56) = 0.30, \mu_{Mo}^3(65) = 0.48$ and $\mu_S^3(65) = 0.65, \mu_N^4(20)$ $= 0.80$ and $\mu_M^4(20) = 0.33$.

Table 2: Rule base for n = 4 example

Output of screening test 1	Output of screening test 2	Output of screening test 3	Output of screening test 4	The output of the inference
Mild	Moderate	Moderate	Normal	Mild
Mild	Moderate	Moderate	Mild	Moderate
Mild	Moderate	Severe	Normal	Moderate
Mild	Moderate	Severe	Mild	Moderate
Mild	Severe	Moderate	Normal	Moderate
Mild	Severe	Moderate	Mild	Moderate
Mild	Severe	Severe	Normal	Moderate
Mild	Severe	Severe	Mild	Moderate
Moderate	Moderate	Moderate	Normal	Moderate
Moderate	Moderate	Moderate	Mild	Moderate
Moderate	Moderate	Severe	Normal	Moderate
Moderate	Moderate	Severe	Mild	Moderate
Moderate	Severe	Moderate	Normal	Moderate
Moderate	Severe	Moderate	Mild	Moderate
Moderate	Severe	Severe	Normal	Moderate
Moderate	Severe	Severe	Mild	Moderate

With 4 tests, now there are $4^4 = 256$ rules, although according to the membership degrees above only sixteen of these rules are needed in this example, listed in Table 2. Using these rules and min-max operators, this patient belongs to the "mild" and "moderate" fuzzy sets with membership degrees from rule 1 and rules 2-16, respectively, of

$$\mu_{\mathrm{M}} = min(\mu_M^1(Q_1), \mu_{Mo}^2(Q_{12}), \mu_{Mo}^3(Q_{31}), \mu_N^4(Q_4)) = min(0.5, 0.76, 0.48, 0.80) = 0.48 \tag{4}$$

and

$$\begin{aligned}\mu_{\mathrm{Mo}} &= max\{min(\mu_M^1(Q_1), \mu_{Mo}^2(Q_{12}), \mu_{Mo}^3(Q_{31}), \mu_M^4(Q_4)) \ldots min(\mu_{Mo}^1(Q_1), \mu_S^2(Q_{12}), \mu_S^3(Q_{31}), \mu_M^4(Q_4)) \\ &= max\{min(0.5, 0.76, 0.48, 0.33), \ldots min(0.75, 0.30, 0.65, 0.33)\} = 0.65.\end{aligned} \tag{5}$$

These fuzzy values then are converted into a crisp value using any of the defuzzification methods mentioned above. Using the COG (Eq. (2)) and MOM methods, the final trauma severity degrees calculate to be 44.75 (shown below) and 50.88, respectively, both of which indicate a final diagnosis of "moderate trauma" using the expert-based scale from Guler et al [7], shown in Table 3. Using the FOM and LOM methods, however, the final trauma severity degrees are 43.00 and 58.75, respectively, corresponding to "moderate" and "severe" trauma on this scale. Thus, the final diagnosis can depend on the defuzzification method. Table 4 summarizes how the final diagnosis at time t_i can change over time as the above screening test results are incorporated into the fuzzy inference system as they become available, presumably becoming more accurate over time.

$$z_{CG}^{*} = \frac{\int_{15}^{22.2}\left(\frac{x}{15}-1\right)xdx + \int_{22.2}^{39.6}0.48xdx + \int_{39.6}^{43}\left(\frac{x}{20}-\frac{3}{2}\right)xdx + \int_{43}^{58.75}0.65xdx + \int_{58.75}^{75}\left(-\frac{x}{25}+3\right)xdx}{\int_{15}^{22.2}\left(\frac{x}{15}-1\right)dx + \int_{22.2}^{39.6}0.48dx + \int_{39.6}^{43}\left(\frac{x}{20}-\frac{3}{2}\right)dx + \int_{43}^{58.75}0.65dx + \int_{58.75}^{75}\left(-\frac{x}{25}+3\right)dx} = 44.75 \tag{6}$$

Table 3: Expert-based scale for trauma severity degrees

Trauma severity degree	$Q < 15$	$15 < Q < 40$	$40 < Q < 55$	$55 < Q < 85$
Decision	Normal	Mild	Moderate	Severe

Table 4: Example of changes in diagnosis over time and according to defuzzification method for one patient

Time	**Screening test 1**	**Screening test 2**	**Screening test 3**	**Screening test 4**	**Final Diagnosis**			
					COG	**MOM**	**FOM**	**LOM**
t_1	45	(not yet available)	(not yet available)	(not yet available)	Moderate	Moderate	Moderate	Severe
t_2	45	56	(not yet available)	(not yet available)	Severe	Moderate	Moderate	Severe
t_3	45	56	63	(not yet available)	Moderate	Severe	Severe	Severe
t_4	45	56	63	20	Moderate	Moderate	Moderate	Severe

3.3 Model evaluation, Tuning, and Optimization

Clearly, intermediate and final diagnoses can be fairly dependent on all $4n$ membership function shapes and $16n$ parameters (a, b, c, d), n intermediate and final rules-bases, and n defuzzification scales (all potentially decision variables). To evaluate model accuracy, resultant diagnoses for a large cohort of patients could be compared to their ultimate known states (such as using a final expert consensus as a gold standard for comparison), such as illustrated in Table 5. Overall and severity-specific evaluation criteria could include the percent of correct diagnoses, the predicted-actual mean deviation (or mean squared or mean absolute deviation), or either of these for each specific severity level; i.e., presumably with correct diagnoses of mild TBI being of particular interest.

Table 5: Example of evaluation and optimization of the rule base (n = 2 case)

$$min.\, z = \sum_{\{j|O_{1j}=k, O_{2j}=l\}} (x_{kl} - r_j)^2 \quad \forall\, k, l$$

subject to

$$x_{kl} \le 4$$
$$x_{kl} \ge 1 \text{ and integer.}$$

Patient (j)	Output of Screening Test 1 (O_{1j})	Output of Screening Test 2 (O_{2j})	Real State (r_j)
1	1	2	Normal – 1
2	2	1	Mild – 2
3	1	2	Mild – 2
4	3	4	Moderate – 3
⋮	⋮	⋮	⋮

Additionally, performance could be improved or optimized by searching out the values of some or all of the above decision variables to optimize each of the above performance criteria, such as to minimize the number of undetected or misdiagnosed cases. Several models could be developed to optimize membership function values, rule bases, and defuzzification scales – the optimal values of which might be different for each intermediate and final number of screening tests (*n*). By example, an optimal rule base might be developed using a quadratic mathematical model that minimizes the square errors, as shown below, where even in this simple case the number of decision variables may be as many as 4^n. Different solutions based on the above different criteria also could be weighted or traded-off against one another using various multi-criteria or desirability approaches. More broadly, note that the number of decision variables potentially could grow exponentially, depending on how exhaustive the model is, and that special heuristics may be necessary to find optima.

4. Conclusion

Determining the existence and severity of TBI is extremely important, both in the military and more broadly. Undetected and untreated, TBI may put a soldier or his unit at risk, as well as cause irreversible damage. Higher severity cases are more likely to be detected, but many patients having mild TBI can go undetected for some time. Current methods, which in fact generally are fuzzily-interpreted by field and medical personnel, may be insufficient or at least not uniformly practiced in practice. Additionally, information from single stage screenings may not always be optimally considered along with other test results.

A sequential screening procedure such as that described above could make a significant contribution to the safety and long-term well-being of U.S. servicemen. To realize this potential, further work should be conducted to more fully develop this modeling framework, evaluate and optimize its performance, and implement it in a user-friendly decision-support tool for deployment. Other classifier methods that might serve similar purposes also should be researched and compared, such as multinomial categorical logistic regression and neural networks in particular.

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