Transferable Belief Models for Human Welfare Assessment with Wearable Sensors

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Abstract - This paper describes the use of the transferable belief model in its discrete and continuous forms for fusing and classifying data and information from various wearable sensors that allow for an assessment to be made on the welfare of the user. Data and information is received from sensors and systems that report on individual factors that can affect the user of the wearable sensor system. Some of these are time related and so can be fused at each time step, while others will only be classified, both of which are then fused to allow welfare analysis to take place. Decisions regarding the ability of the user to perform tasks can be made dependant on the results of this analysis, as well as the need for the user to receive medical assistance or support from fellow workers.

Keywords: transferable belief model, welfare, bio-med, impact alarm

1 Introduction

Most civilian and military personnel currently use multiple stand alone systems for communications, intelligence gathering and personal protection. Integration of these into a single platform will provide benefits from on board processing and fusion allowing smart systems to be created that will increase situation and user welfare awareness, while at the same time reducing the burden on the user. A lightweight protective carrier that has core sensors embedded into it, along with processing, power and communications will fulfill the needs of such a platform, as shown in Figure 1. A prototype of the protective carrier can be seen in Figure 2. The core sensors will look at the biological/medical performance of the wearer, as well as a strike alarm system that detects and reports on strikes on the user from both ballistic and non ballistic objects, while at the same time giving an indication of the type of activity being undertaken and the pose of the user.

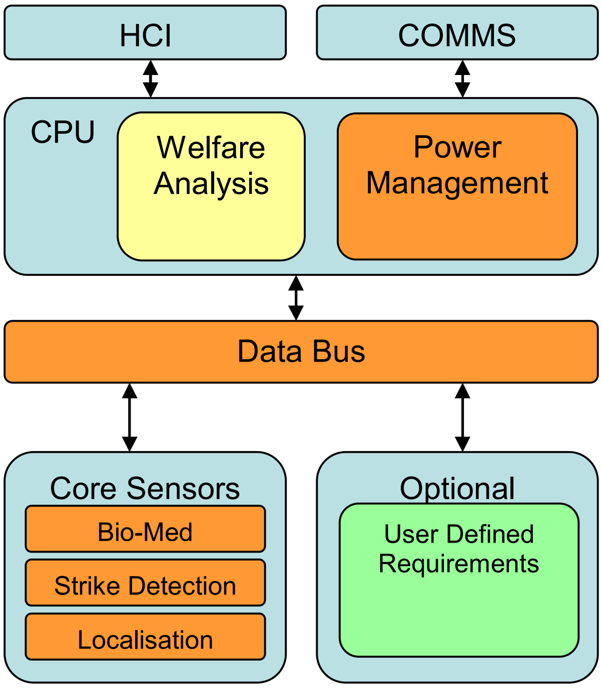

Figure 1. Welfare analysis within wearable protection and sensor system

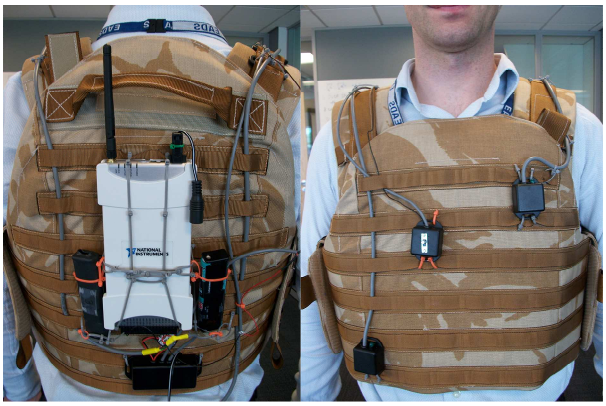

Figure 2. Wearable Sensor System Prototype

Combining these data sources together will show the level of physical and mental stress that the user is experiencing, as well as flagging critical and non-critical injuries, as shown in Figure 3. This information is communicated to the control centre where a decision can be made about the need to assist the user.

2 Paper Outline

In Section 3 we present the basic building blocks of the transferable belief model, in both its continuous and discrete forms. In Section 4 we discuss the data that is available to the system and how models are applied and fusion is performed. In Section 5 we present the results and in Section 6 conclusions are made.

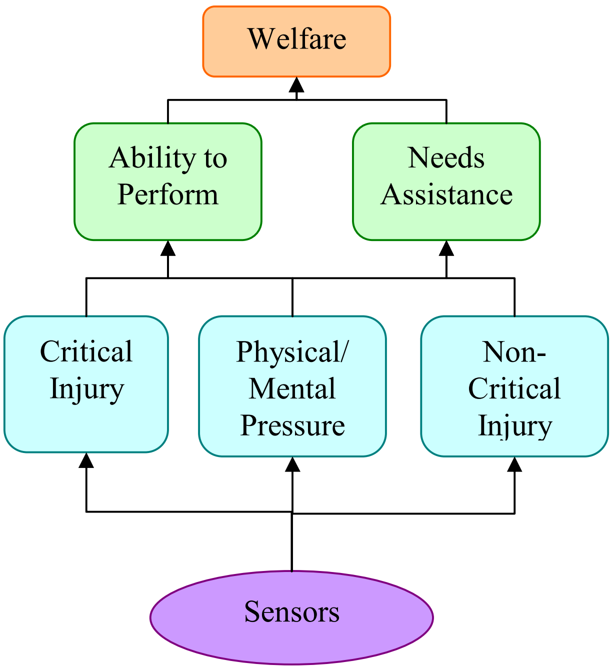

Figure 3. Fusion and classification within the welfare system

3 Transferable Belief Model

The transferable belief model (TBM) [1] is an extension of Dempster Shafer Theory (DST) [2,3]. The extension allows for an open world to be entertained where we can model the world that we know about, but also leave the possibility for the truth to be something outside of that world. This is something that is not possible in DST and is discussed previously [1,4,5]. The TBM also allows for the possible outcomes to be altered during the process, thus hypothesis that are no longer possible can have their belief transferred to the remaining possible hypothesis. The TBM operates on a *credal* and *pignistic* level where beliefs on hypothesis of the outcome are entertained at the *credal* level and decisions on the truth are made at the *pignistic* level.

3.1 Discrete Transferable Belief Model

The TBM is a set based approach where beliefs are assigned to sets of possible hypothesis. The set of all possible hypothesis and their combinations is the power set, Θ, which has 2^n sets within it, n is the number of singletons, where a singleton is each of the individual possible outcomes that we account for and the set of all possible outcomes is the Ω. Each of the sets within the power set Θ is assigned an initial mass, m, giving us a basic belief assignment (*bba*), such that

$$\sum_{A \subseteq \Theta} m(A) = 1 \qquad (1)$$

The mass, m, assigned to each of the sets is the proportion of all relevant evidence that supports that proposition. A set with more than 1 element signifies that the outcome is one of the singletons within that set, but we have no evidence to say which one. The length of these sets is an indicator to the vagueness, or uncertainty that we are placing our belief on. If the set has many elements then we are vague on our decision, if the set has only one element and we place mass on it then it is displaying certainty.

When decisions are to be made on the bba the pignistic transform is used to create probabilities from the bba for each of the sets within it

$$BetP(A) = \sum_{X \subseteq \Omega} \frac{|A \cap X|}{|X|} \frac{m(X)}{1 - m(\varnothing)}, X, A \neq \varnothing \qquad (2)$$

3.2 Continuous Transferable Belief Model

Many applications are not efficiently represented in a discrete space and thus the discrete TBM has also been extended to cater for continuous variables [4,6,7] as input parameters, which a mass can be assigned to. When working with continuous spaces the *bba* is applied to a belief triangle, see Figure 4. This is a convenient representation, and helps when visualizing the masses you are assigning in the continuous space.

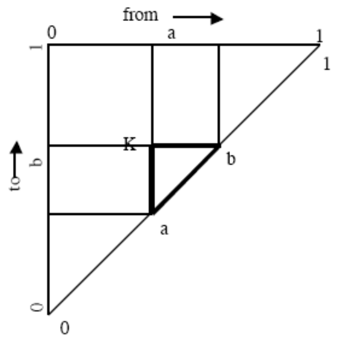

Figure 4. The belief triangle for continuous spaces

Figure 4 shows how intervals and their masses can be placed within the belief triangle for values within the range *[0,1]*. A mass can be assigned to the point K which is for the interval *[a,b]*. Where *a=b* the mass is for a single continuous value. This can be extended to the range $[-\infty,\infty]$ to allow for all real valued numbers including infinity. If instead of having points like K to give masses for each point value we use a density function then we can create a real valued continuous bba density. Where previously we were working with summations we are now looking at integrals.

3.2.1 Classification in the Continuous Transferable Belief Model

The continuous TBM allows us to use prior information in the form of Probability Density Functions (PDF) for each of the classes that are in consideration. From these we can create the conditional bbas for each class across the belief triangle. These bbas, conditioned on class, allow for the conditional probability density functions to be generated such that given an input variable we can output the probability of its membership to each of the classes that we are classifying against, and have supplied a PDF for.

3.3 Fusion in the Discrete Transferable Belief Model

Information and data is fused at varying points and levels within the Welfare Analysis System. There are various methods for performing this fusion as described in various texts [8,9,10]. These methods all differ slightly in their operation and how they handle open worlds, closed worlds and the empty set [5]. These fusion operators only work in the discrete domain so all of our fusion in the Welfare System will take place at this level, even though we can take continuous values as inputs.

4 Welfare Analysis

The welfare of a user of the wearable sensor system is determined by analysis of the inputs provided by the components of the system. Some of these components will provide raw data from their sensors, but others will process the data and supply higher level information. Analysis of the welfare of the user will therefore have to utilize raw sensor data and information (processed data) in both the discrete and continuous domains. The final outcome of this analysis will enable an evaluation of the physical and mental state of the user. This is shown by two outputs:-

1. Ability of the user to perform their duty
2. Necessity to receive assistance

The processing of data through preceding TBMs, that feed into these two higher level decision TBMs is shown in Figure 3

4.1 Data Inputs

The building blocks of the fusion system are shown in Figure 3. Similarly a more detailed view of the system map is given in Figure 5. Here all of the classifier elements are shown in their hierarchical grouping. This shows how data and information will feed through the system to make the decisions at each level, before they are passed on.

Following in this section the input parameters for the fusion system are described. Generally the inputs are normalized to a scale of 0-100, where 100 is severe and 0 is nonexistent.

There are also multiple classes described where each class has an *n*-dimensional univariate Gaussian PDF associated with it. These distributions describe each class with respect to the parameters. This allows for a distinction to be made between classes, and is how the classification takes place.

The classification of a critical injury takes in information from the strike detection module. This provides information on the area of the impact in 4 quarters on the front upper body, taken *as upper left (UL), lower left (LL), upper right (UR) and lower right (LR*). We assign the likelihood of critical injury from this area if a strike occurs on a 0-100 scale as shown in Table 1. In the future this will become a distance and direction measure from the centre of the vest. Future research will allow for a medically based model to be created of the torso. This that maps xxxxxxxxxxxxxxxxxxxxxxxxxxxxxx

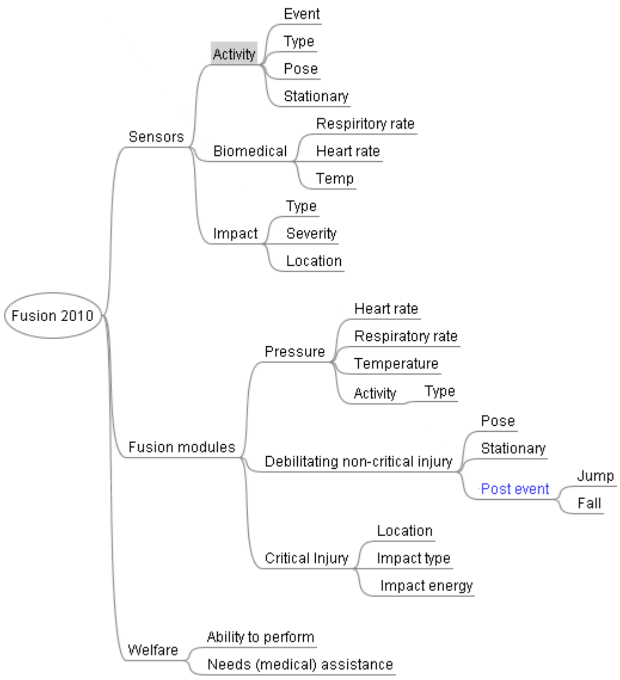

Figure 5. Map of the data used within the Welfare Analysis

Table 1. Critical Injury likelihood due to Location on torso of Impact

UL	***UR***	***LL***	***LR***
90	60	25	25

The second input for the critical injury classification is taken from the type of impact. The possible options are *Blunt Object (BO), Sharp Object (SO), Low Velocity Ballistic (LVB) and High Velocity Ballistic (HVB)* [11]. Again these are assigned a likelihood of critical injury on a scale of 0-100 and are shown in Table 2

Table 2. Critical injury likelihood due to type of strike object

BO	***SO***	***LVB***	***HVB***
10	25	60	95

Finally we take the energy from the impact as a factor. Each type of object that can strike the torso has a related (normalized to 0-100) impact energy. These have mean and standard deviation as shown in

Table 3. Normalised strike energy delivered by strike object types

	BO	***SO***	***LVB***	***HVB***
Mean	10	50	25	80
Std	5	5	0	5

These three inputs are used to create a continuous valued TBM in 3 dimensions, with prior PDF's for the classes of *Good*, *Bad* and *OK*, relating to the severity of critical injury (with respect to being critical) sustained as shown in Table 4. Again the *Energy*, *Type* of impact and *Location* are on a scale of 0-100

Table 4. Prior PDF parameters for severity of critical injury (criticality)

	Energy	***Type***	***Location***
Good-Mean	5	20	20
Good-Std	20	20	20
OK-Mean	30	50	50
Ok-Std	20	20	20
Bad-Mean	80	75	75
Bad-Std	20	20	20

The non-critical injury classifier takes input from the movement of the user where a likelihood scale of 0-100 relates movement, or lack of it, to having obtained an injury, shown in Table 5

Table 5. Likelihood of movement signifying a non critical injury

Movement	***No Movement***
10	95

The second non-critical injury input is the pose of the user. This is given as 4 different possible positions, again their likelihood, on a scale of 0-100, to signifying an injury has occurred are shown in Table 6

Table 6. Likelihood of pose signifying an injury

Standing	***Kneeling***	***Sitting***	***Lying***
5	50	30	90

Finally the non-critical injury classifier receives information on the type of event that has just occurred. This is either a *jump* or a *fall*. Each of these can cause injury and their likelihoods, on a scale of 0-100, are shown in Table 7

Table 7. Likelihood of an event causing injury

Jump	***Fall***
65	50

These are taken as inputs to a continuous valued TBM in 3 dimensions, with prior PDF's for the classes of *Good*, *Bad*, and *OK*, relating to the severity of a non-critical injury, on a scale of 0-100, as shown in Table 8

Table 8. Prior PDF parameters for non-critical injury

	Pose	***Movement***	***Event***
Good-Mean	20	20	20
Good-Std	20	20	20
OK-Mean	40	40	40
Ok-Std	20	20	20
Bad-Mean	100	100	100
Bad-Std	30	30	30

The final system is looking at fusing over time, and classifying, the pressure that the user is under [12]. This takes inputs from bio-med sensors which give *heart rate* (*HR*), *respiratory rate* (*RR*) and external body *temperature*, as well as information on the type of activity. We are able to switch the models that we use based on the activity to classify the pressure (exertion) as *low*, *medium*, or *high*. The prior PDF's used for each model and the classes are shown in Table 9, Table 10 and Table 11.

Table 9. Prior PDF parameters for Pressure of a person running

	HR(bpm)	***RR(breath pm)***	***Temp (degrees C)***
Low-Mean	100	30	36
Low-Std	20	20	4
Medium-Mean	115	35	38
Medium-Std	20	20	4
High-Mean	150	40	40
High-Std	20	20	4

Table 10. Prior PDF parameters of a person walking

	HR (bpm)	***RR (breaths pm)***	***Temp (degrees C)***
Low-Mean	80	20	34
Low-Std	20	20	4
Medium-Mean	105	25	36
Medium-Std	20	20	4
High-Mean	120	30	38
High-Std	20	20	4

Table 11. Prior PDF parameters of a stationary person

	HR (bpm)	***RR (breaths pm)***	***Temp (degrees C)***
Low-Mean	65	15	32
Low-Std	20	20	4
Medium-Mean	75	20	34
Medium-Std	20	20	4
High-Mean	85	25	36
High-Std	20	20	4

4.2 Welfare Analysis Parameters

The welfare of the user is taken as presenting to an analyst the ability of the user to perform their duty and if there is a need for assistance. Both of these fuse over time the outputs from the critical injury, non-critical injury and also the pressure modules as detailed in the previous section. The two outputs are aligned quite similarly to the inputs but have a different weighting placed on the importance of their inputs. This is performed by discounting the incoming information as shown in Table 12 where 1.0 is a complete discount.

Table 12. Discounting factors for ability to perform and assistance modules

	Critical Injury	***Non-critical Injury***	***Pressure***
Assistance Required	0.1	0.5	0.9
Ability to Perform	0.05	0.1	0.15

5 Results

The following results show the output from the modules used in the fusion system at the varying levels of fusion and classification. To aid visualization the scaling of the Y axis is normalized to scale from 0-100, which includes the masses and probabilities that are shown along side the input data.

5.1 Fusion and classification at the lower level

Figure 6 shows the output from the non-critical injury classifier. The masses for the singleton sets are shown for *Good*, *OK* and B*ad* and the inputs for *Pose*, *Movement* and *Event*. We can see that classification changes to Bad after the event occurs at time 14.

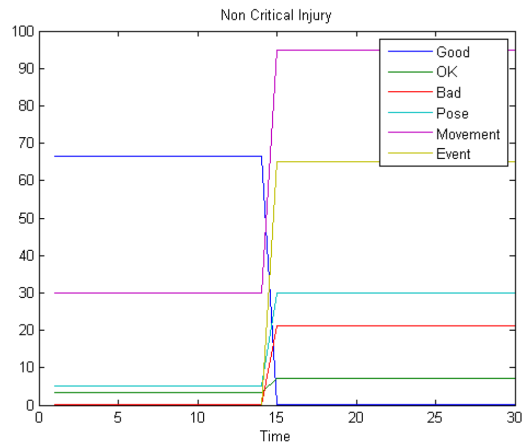

Figure 6. Non-critical injury classification

Figure 7 shows a critical injury occurring at time 20 which changes the classification to *Bad*, where it will remain as a threshold limit has been reached. Once a critical injury has been classified then we do not want the system to recover to a different state for reasons of human safety.

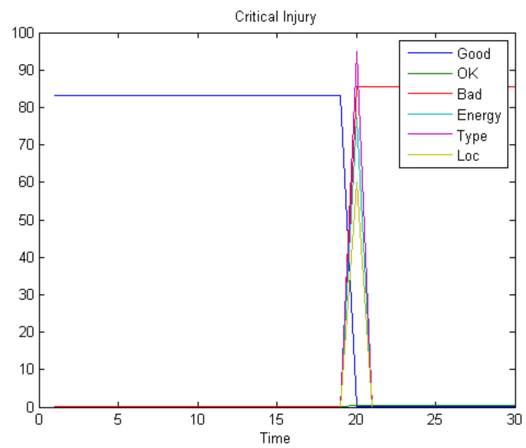

Figure 7. Critical Injury Classification

Figure 8 shows the fused output from the pressure classification. The person doesn't show any particular changes in his vital signs but his temperature is quite high putting him under some stress physical and mentally.

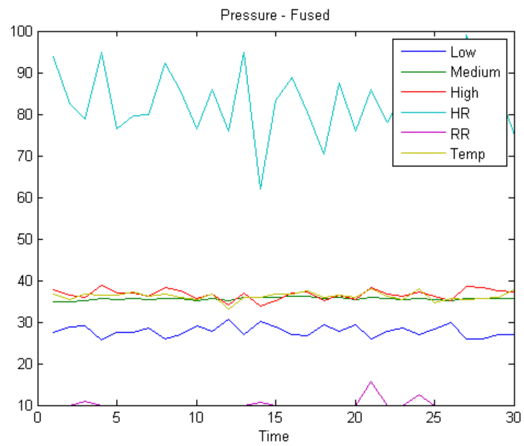

Figure 8. Fused pressure for a relatively stressed person

5.2 Welfare output Scenario 1

A non-critical event occurs at time 3 which is classified as being *Bad* and a strike is received at time 28, but this is classified as *Good* in terms of criticality. The vital signs remain relatively stable throughout with pressure being *Medium*. The fused outputs clearly show where the 2 events took place and the systems response to these events. We see that Figure 9 shows that the user does not require assistance after the first event, which was related to a non-critical injury, but once the addition of the strike occurs that person does require assistance, even though the strike itself was not classified as critical. Figure 10 shows that the user's ability to perform the duty has been severely degraded due to the first event to the extent that they cannot perform their duty any more.

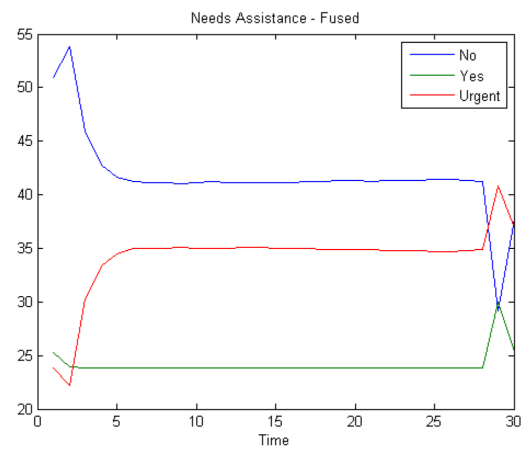

Figure 9. Necessity to receive Assistance

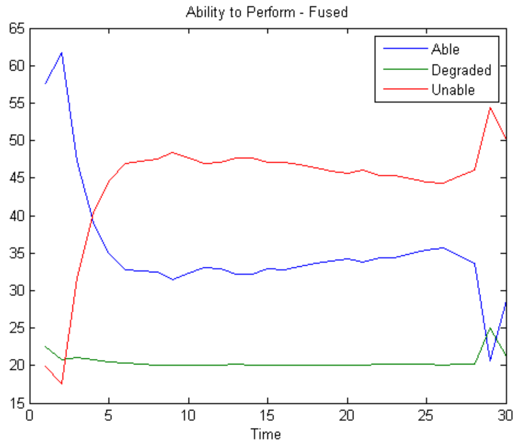

Figure 10. Ability of the user to perform their duty

5.3 Welfare output Scenario 2

Figure 11 and Figure 12 show the welfare of the user after receiving a non-critical event and a strike, but these are not severely impacting as the user recovers from the events quite quickly. The non-critical event occurs at time 12 and the strike occurs at time 22. We can see that the system allows for the recovery of the user to be mirrored with the welfare outputs that both show this recovery.

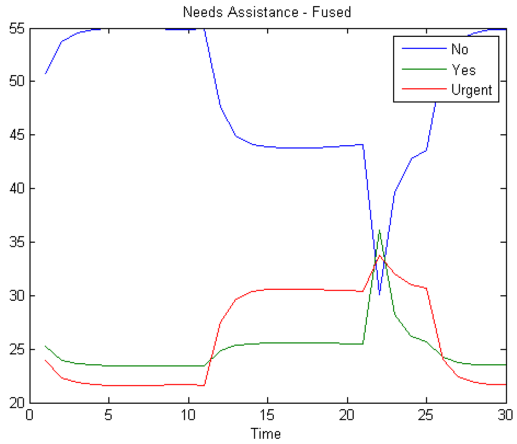

Figure 11. Necessity to receive assistance

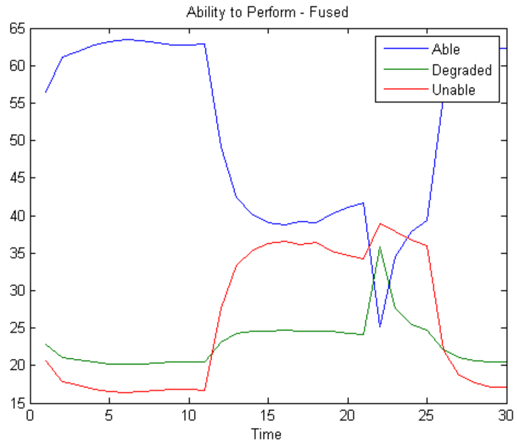

Figure 12. Ability of the user to perform their duty

5.4 Welfare output scenario 3

The final scenario is of a user who receives a severe non-critical and critical injury at around the same time, time 12. All classifiers signify that this is severe for the rest of the time frame. Figure 13 and Figure 14 show how quickly the system can respond to such a severe incident and remain showing this high probability of needing assistance and being unable to perform their duty.

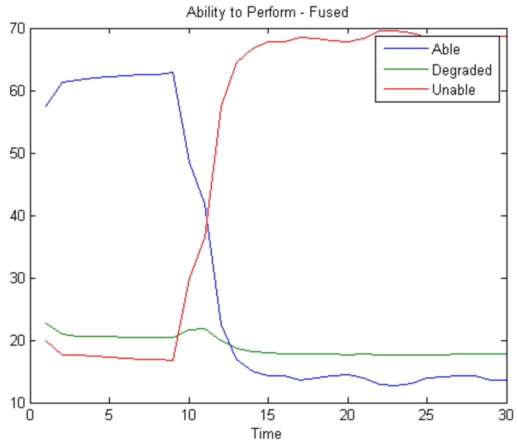

Figure 13. Ability for the user to perform their duty

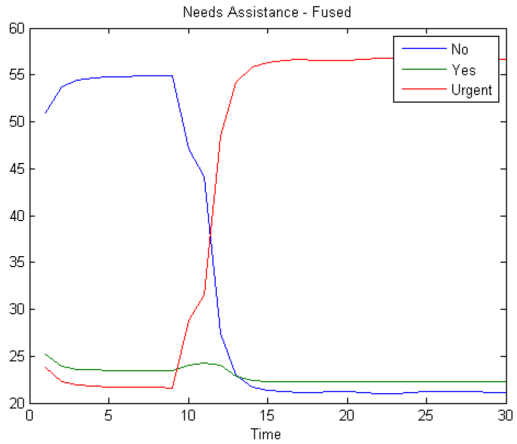

Figure 14. Necessity to receive Assistance

6 Conclusion

We have shown that we can receive inputs from a large variety of sensors, in varying formats and effectively fuse and classify using discrete and continuous TBMs. The system is shown to make logical decisions related to these inputs and events that occur with respect to the user of the wearable sensor system. The architecture of the system allows for it to be fully adjustable to account for the individual users. This may be related to their fitness levels and abilities to cope with stress.

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