Estimating (Human) Cognitive States in a Human-Machine System: A Fuzzy Modeling Approach

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Abstract

A fuzzy model for evaluating and estimating the human operator states in a human-machine system is proposed. The major parts of the model consist of subjective evaluation of the human 'perception' of task, the translation of the subjective data to fuzzy membership functions, and the application of an intuitive heuristic to determine the desired operator states. The model efficacy is demonstrated by experimenting with the human operator cognitive states in a pursuit tracking task.

1. Introduction

Due to increasing levels of automation, the human roles in human-machine systems have shifted increasingly towards mental tasks, such as tracking the behaviors of the system sensors (observing, inspecting, and monitoring). The task of the human operator has become more abstract and the required skills more cognitive. With these changes in human roles, and with the availability of "intelligent" decision aids in human-machine systems, one of the several concerns by system designers and analysts is, "what is the human operator performance?"

Research in human workload, see, for example, Welford (1978), Moray (1982), and Hancock and Chignel, (1988) have attempted to evaluate the human operator states as a composite set of psychophysical, psychological, and cognitive variables in workload equations. Generally, it is assumed that human perception of the task domain affects workload. Because of this assumption of behavioral and subjective measurements, workload modeling has become multidimensional in scope; often utilizing modeling techniques such as, statistical factor loading, multidimensional scaling, and correlation analysis.

It remains increasingly clear that workload, if reliably measured, calibrated, and integrated into a human-machine system design as a function of dynamic task module, can provide the basis for assessing the human and machine performances. As echoed by Russell, Wilson, and Monett (1996), "Accurate and reliable, assessment of operator state is the key to successful implementation of adaptive automation".

1.1. The catalyst in workload modeling

In order to use workload measures as standard for prediction of performance in human-machine systems, it is important to assess and understand the levels within a task dimension which the human performs and contributes to the overall system goal. This will help the system designers and analysts to determine the levels which machines can be used to assist the human operator. As an example, consider the pilot in the supervisory monitoring tasks, who in case of automation failure must also perform a single-axis compensatory tracking task. In addition, assume the pilot is performing flight handling tasks in an adverse weather conditions involving poor visibility, storms and lightning, and a mountainous flight segment. This simplified but extreme scenario constitutes, in addition to the task requirements, the basic workload generating functions (WGFs) to the pilot. The WGFs have no common scale of measurement; they are dynamic; unpredictable (to some degree), and most often, co-vary with one another. The basic (single) predictable measure of workload is therefore a complex modeling problem. However, in some sense, the pilot can subjectively determine his/her state of workload. The subjective data need to be transformed into a general metric. For this kind of problem, fuzzy (set) models have been found to be more robust and sensitive (Moray, 1982; Turksen, Moray and Krushelynycky, 1988).

2. Sample Past Studies

Determining human operator states in a complex human-machine system depends for the most part on post hoc self evaluation data. Human self evaluation has been determined by psychologists (Kelly, 1955) to provide more sensitive and robust metric for measuring human perception of task.

Wang, Sharit and Drury (1991) designed a study with inspection tasks to measure cognitive factors that account for inspection performance. A fuzzy set model formulated as multicriteria decision making problem was utilized to determine whether individuals can prioritize cognitive skills considered important for inspection performance. Results indicated a close correspondence between fuzzy set and statistical approaches, suggesting the possibility for integrating the individual's subjective appraisal of the relative importance of cognitive factors.

Success obtained in the applications of fuzzy models to workload modeling (Thurksen, Moray, and Krushelynyky, 1988), and human performance metric (Mital and Karwowski, 1986) favors the continuous investigation of fuzzy set theory as a formal method for modeling, describing, analyzing, and quantifying human dimensions in a system design (Thurstone, 1927).

3. A Heuristic Fuzzy Model For Human Cognitive States

The heuristic fuzzy model is developed with a single macro assumption: the task domain determines how the human operator evaluates his/her performance after experiencing direct interaction (control and execution) of the tasks. Similar to Wang, Sharit, and Drury (1991), cognitive states of the human operator shall be modeled using a fuzzy (subjective) assessment metric.

Modeling human cognitive states is particularly important in supervisory control tasks requiring monitoring, perception, judgement, attention and memory resources. The problem of prioritizing cognitive factors with respect to their relative importance to performance is strongly encapsulated within human self assessment. This can be achieved through after-the-fact task performance.

3.1. The experiment task

The sample experiment was a pursuit tracing task investigated by Ntuen and Watson (1996). Twenty subjects (8 males and 12 females undergraduate and graduate students at North Carolina A&T State University) were selected randomly for the experiment. The subjects ranged from ages 18 through 30 years old. Subjects participated voluntarily.

The equipment used in this experiment included a Manual Control Laboratory (MCL) and the Aggie Flight Simulator Platform (AFSP). An IBM compatible computer, color graphics board, and monitor, math processor, and mouse were required to run the MCL Software.

In the pursuit tracking task, subjects attempted to position the cursor inside a rectangle target. Both the cursor and target were subjected to pseudo-random disturbance. The subjects performed each task set at four levels of difficulty under four different control orders: zero, first, second, and third order. Within the dynamic parameters, the open-loop gain, damping factor stiffness factor, prediction/quicker cursor, position, velocity, acceleration, and control time delay were fixed for each control order. The levels of difficulty were introduced by varying the disturbance over the amplitude of the target and cursor. The disturbances over amplitude values ranged from 0.0 to 1.0 half-screen heights. Higher values result in a larger effect of the disturbance. The disturbance parameters remained at the fixed levels provided by the MCL Software.

3.2. Subjective data collection

After each experimental trial, the subjects were asked to rate their perception of frustration on a cognitive scale that varies from "very low" to "very high". A numerical scale was assigned to each of the subjective scale as follows:

Very low (0-2), Low (2^+ - 4, Moderate (4^+-6) High (6^+-8), and very high (8^+-10). The "+" indicates greater than. The cognitive variables selected for assessment are similar to those of Wang, Sharit and Drury (1986) as follows:

1. cursor positioning, (b) estimate the difference between the target and control locations, (c) envision or predict the direction of target relative to control, and (d) detect error during tracking.
2. Perception. The means by which information acquired from environment via the sensor organs is transformed into experiences of objects, events, etceteras. The perceptual factors measured were (a) direction of relative motion between target and control, (b) visual perception of speed between target and control, (c) spatial perception of path geometry in pursuit of the target, and (d) perceptual control of error in the tracking path.
3. Attention. In supervisory control tasks such as monitoring, a large amount of attentional resources are required for pursuit tracking. The following human operator states were assessed: (a) speed of response, (b) anxiety, (c) vigilance, and (d) concentration (focus of attention).
4. Memory. To some degree, pursuit tracking requires a continuous state of information processing requiring such abstract tasks as: (a) recall of directions, (b)

recall of orientation in object location in space, (c) visual information load, and (d) integration of information from various and changing spatial points.

Table 1 shows the statistics (averages and standard deviations) of the subjects' rating of their frustration level in a second-order pursuit tracking task. The results is for ten (10) repeated trials per subject with random variations in levels of task difficulty as controlled by MCL damping factors.

Table 1. Sample average ratings of frustration (on a pursuit tracking task)

Cognitive Variables	Subjective Scale: Very low (0-2) Mean	Std	Low (2^+ - 4) Mean	Std	Moderate (4^+ - 6) Mean	Std	High 6^+ - 8) Mean	Std	Very High (8^+ - 10) Mean	Std
Judgement:										
Estimating position	0	0	2.11	1.53	5.38	1.70	7.25	0.91	8.67	1.2
Estimating differences	1.34	0.44	3.64	0.18	4.86	0.25	6.90	1.33	8.29	0.84
Envisioning direction	0	0	2.33	2.21	5.23	1.66	7.82	0.67	8.41	2.30
Detecting error	0	0	2.50	1.9	4.11	0.89	7.41	1.88	8.61	2.14
Perception:										
Direction of relative motion	1.83	0.26	2.36	0.49	4.18	1.82	7.61	1.58	0	0
Visual perception of speed	2.60	1.1	3.15	1.36	4.62	1.67	7.45	1.44	0	0
Perception of path geometry	1.0	0	3.15	0.67	5.15	0.94	6.98	1.29	0	0
Perceptual control of error	2.45	1.21	3.84	2.11	4.22	1.23	7.24	0.96	0	0
Attention:										
Speed of response	1.87	0.64	3.43	0.68	4.18	0.95	7.94	1.25	8.70	1.60
Anxiety	1.55	0.91	2.69	0.93	5.11	1.26	7.66	1.66	9.15	1.33
Vigilance	0	0	3.11	1.01	4.39	1.40	7.27	0.94	9.24	2.51
Concentration	0	0	3.74	0.52	4.73	1.29	6.24	1.35	8.64	2.33
Memory:										
Recall direction	1.90	0.24	3.29	0.17	5.67	1.24	7.67	1.21	9.23	2.11
Recall orientation	2.64	1.33	2.29	0.64	5.35	0.94	7.25	2.4	8.47	0.94
Visual memory load	1.21	0.41	2.81	0.91	4.93	0.87	7.76	1.02	8.92	1.47
Information integration	1.88	0.95	2.96	0.22	5.21	1.22	6.94	0.99	8.38	1.24

3.3. Transforming rating data into degrees of membership (fuzzy measure)

The subjective ratings of each attribute was transformed into a fuzzy measure using the degree of membership heuristic (DMH) developed by Ntuen and Chestnut (1995). The DHM fuzzy function is defined as

$$\mu_i(x) = \begin{cases} \dfrac{\sum_{j=1}^{m}\left\{\sum_{i=1}^{n}\dfrac{S_{ij}}{\max_j}\right\}S_{ij}}{\sum_{j=1}^{m} S_{ij}} \quad , \quad for\ i > 1 \\ \sum_{j}\left(\dfrac{S_{ij}}{\sum_{j=1}\max_j}\right) \quad for\ i = 1 \\ 0 \quad , \quad otherwise \end{cases} \tag{1}$$

where $\max_j$ is the upper interval limit on the scale multiplied by the number of rated variables, n is the number of rated variables in a cognitive set, M is the number of options in the rating scale, S_{ij} is the rated value of variable i in the scale interval j. As an example, consider the perception variables in Table 1 whose mean values are reproduced here:

Table 2. Ratings of perceptual attributes

	Very low (0-2)	Low (2^+ -4)	Moderate (4^+ -6)	High (6^+ - 8)	Very High (8^+ - 10)
Direction of relative motion	1.83	2.36	4.18	7.61	0
Visual Perception of speed	2.6	3.15	4.62	7.45	0
Perception of path geometry	1.0	3.15	5.15	6.98	0
Perceptional Control of error	2.45	3.86	4.22	7.24	0

Assume the posterior ratings of task as follows:

Task Attribute	Membership value
Information content	0.54
Difficulty	0.90
Time constraint	0.75
Complacency	0.60
Risk	0.55

In order to calculate the membership values of the factors in Table 2, each factor is conceptually mapped to each task attribute since each cognitive factor is rated based on the perception of the task attributes. Conceptually, we have a fuzzy relation such that

$$S: X \rightarrow Y$$

where X is the subjective cognitive factor, and Y is the task measures, and S < s_{ij} > is one to many mappings between each cognitive factors to the task attributes with X < x_i, i = 1, 2, … M >, Y< y_k, k = 1, 2, … K >. Heuristically, it is more intuitive to calculate the conceptual distance between X and Y using the Hamming distance measure (Tursken, 1986). Thus, we have for each fixed i, say i*, over j domain, define the conceptual distance by

$$d_{i^*} = \left| \sum_{k=1}^{K} y_k - K\mu_i(x) \right| \quad (2)$$

where K is the number of attribute measures in the task category measure, $\mu_i(x)$ is determined from equation (1). As an example, by using Table 2, we have the following values:

Table 3: Sample calculation of $\mu_i(x)$ Equation 2

Cognitive Measure	Degree of Membership $\mu_i(x)$
Direction of relative motion Visual perception of speed Perception of path geometry Perceptual control of error	0.862 0.86 0.843 0.784

Table 4 shows the calculation of $\mu_i(x)$ for each cognitive measure.

The final stage of the model is to calculate the cognitive state factors. This is obtained as a defuzzification (weighted fuzzy index, see, e.g., Kosko, 1992) value defined in our case by scaling the values of $\mu_i(x)$ with respect to the conceptual distance measures.

$$\Phi_i = \frac{\sum d_i \mu_i(x)}{\sum d_i} \quad (3)$$

For the illustration problem, the calculated human operator (cognitive) states during a pursuit tracking of a second order system has the following parameters as shown in Table 5.

Table 4. Computed grade of membership for cognitive attributes states in Table 1

Cognitive variables	Normalized Membership function
Judgement:	
Estimating position (x_1)	0.848
Estimating differences (x_2)	0.799
Envisioning direction (x_3)	0.846
Detecting error (x_4)	0.838
Perception:	
Direction of relative motion (x_5)	0.862
Visual perception of speed (x_6)	0.860
Perception of path geometry (x_7)	0.843
Perception of control error (x_8)	0.784
Attention:	
Speed of response (x_9)	0.819
Anxiety (x_{10})	0.855
Vigilance (x_{11})	0.898
Concentration (x_{12})	0.877
Memory:	
Recall direction (x_{13})	0.876
Recall orientation (x_{14})	0.884
Visual memory load (x_{15})	0.877
Information integration (x_{16})	0.876

Table 5. Derived cognitive states

Cognitive Factor (Φ)	Cognitive State Measure
Judgment	0.845
Perception	0.843
Attention	0.867
Memory	0.878

4. Conclusion

The existing statistical measures of workload are linear and thus cannot adequately capture the nonlinear behaviors of human-machine systems. For example, they cannot determine the marginal contribution of human operators to the system goal, mostly, in tasks requiring abstract mental resources.

In order to solve this problem, a fuzzy heuristic model is proposed. The aim of the model is to capture human perception of task and how such perception influences cognitive resource utilization during task execution. The weighted cognitive state measure $\mu_i(x)$ has many relevance interpretations and applications:

(a) Workload. The measure $\mu_i(x)$ can be used to assess the most important cognitive variables that contribute to mental workload.

(b) Resource Allocation. The measure $\mu_i(x)$ is a factor that lies between zero and 1. It can be recalibrated into a probability measure and used to: (a) assess the percentage cognitive resources consumed during task execution; and (b) determine the levels of energy entropy due to cognitive tasks; a high energy entropy, for example indicates an increase in level of frustration experienced.

(c) Assessing Human and Machine Performance. The weighted fuzzy data can be translated into a "total probability" measure by considering human opinion on the machine contribution to the system goal.

5. References

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