A FUZZY MODEL FOR WORKLOAD ASSESSMENT IN COMPLEX TASK SITUATIONS

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ABSTRACT

A method for combining subjective measures of workload and task characteristics is described. Data describing the human operator performance in compensatory tracking tasks at three levels of task complexities are used to develop a distribution function of fuzzy workload. The Cooper-Harper (CH) subjective judgment of task difficulty is administered to the subjects after each task completion. The final results show the relationships between fuzzy workload distribution as a function of task complexity.

1. INTRODUCTION

The concepts of workload are characterized by multifaceted definitions (Jex, 1988). This includes the considerations of task characteristics, the human characteristics, and the task environment. Usually, however, workload measures are used to measure human performance This approach has generated various opinions and models, including, but not limited to, mental workload models (Moray, 1979), and physical workload models (Strasser, 1977).

The performance of the human operator is often a concern in human-machine systems. Thus, minimizing workload is considered an important goal in system design (Welford, 1978). For the most part, workload indicators are usually obtained through the subjective ratings of the task characteristics by the person performing the task. For example, how the human operator perceives the level of "difficulty" associated with the task; how much "effort" is required, and the level of "comfort" experienced while performing the task. All these attributes are subjective, imprecise and vague (Moray, Eisen, Money and Turksen, 1988).

Because of the subjectiveness involved in workload measures, it is difficult to a standard workload metric which is stable, sensitive, and global (Jex, 1988). However, recent interest, due in part to the progress in fuzzy set theory (Zadeh, 1973), has concentrated on quantifying the subject workload measures. The paper's contribution to this issue are: 1) assessing the task characteristics, and 2) deriving fuzzy workload measures in an actual experimental condition using the task characteristics. Compensatory tracking tasks at three levels of 'perceived' complexities are used as a proof-of-concept database. The compensatory tasks studied are: position tracking, rate tracking and acceleration tracking. Instability factors are introduced in each task as a measure of complexity. Fuzzy workload distributions are obtained using the workload metric developed by Watson and Ntuen (1996).

2. FUZZY THEORY

Zadeh (1973, 1975) introduced the theory of fuzzy set to address the issues associated with vagueness and impreciseness by hedging subjective opinions on a cognitive scale of preference. Eshrag and Mamdami (1979) developed a general approach to linguistic approximation to weight the "behavioral preference" of choice in multi attribute decision making problem. Others, for example, Baas and

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Kwakernaak (1977) developed methods for ranking subjective alternatives. In general, fuzzy metrics, developed on subjective scales, are known to follow certain laws of comparative judgment (Thurstone, 1927).

The fundamental definitions of a fuzzy set theory are given as follows (Zadeh, 1973):

Let X = {x} be a set of attributes, then a fuzzy set A $\in$ X is a set of ordered pairs

$$A = \{x, \mu_A(x)\}, x \in X \quad ......(1)$$

where $\mu_A(x)$ is called the characteristic function or graded membership of x in A (Zadeh, 1975). The membership function $\mu_A(x)$ maps the fuzzy set A onto the interval [0, 1], that is μ_A: A $\rightarrow$ [0, 1], Similarly, let Y = {y} be a set of criteria variables, then a fuzzy set B$\in$Y is a set of ordered pairs

$$B = \{y, \mu_B(y)\}, \quad y \in Y ...(2)$$

and μ_B: B$\rightarrow$ [0, 1]. Note that $\mu_A(x)$, $\mu_B(y)$ can be assumed to have a known distribution - mathematically or perceptually. The fuzzy distribution can be a real continuous phenomenon or may represent a discrete countable event. The interaction of A and B is defined by:

$$\mu_A(x) \wedge \mu_B(x) = \min\{\mu_A(x), \mu_B(x)\} \quad ....(3)$$

The union of A and B is defined by:

$$\mu_A(x) \cup \mu_B(x) = \max\{\mu_A(x), \mu_B(x) \quad ....(4)$$

The extended maximum operator combines the definitions in (3) and (4). This is defined by :

$$\left.\begin{array}{c}\mu_A(x) \cup \mu_B(x) = Sup\{\min[\mu_A(u), \mu_B(v)]\\ ((u, v / x = \max(u, v), \forall x \in \Re)\end{array}\right\} .(5)$$

3. QUANTITATIVE WORKLOAD INDEX (QWI)

The quantitative workload index (QWI) developed by Watson and Ntuen (1996) is used in this study. The QWI considers the system complexity as a parameter in workload measure. According to Rouse and Rouse (1979), "... complexity is related to the human's understanding of the relationships within a problem as well as the strategy which the human uses to solve the problem (p. 720)". And, the apparent complexity of a system affects how the human operator executes the task (Rasmussen, 1980).

Subjective measures of workload often requires the human operator to evaluate the task according to perceived dimensions of "difficulty". Quite often, the degree of difficulty is confused with, or used interchangeably with degree of complexity. Task difficulty as used here is a measure how the human operator perceives the task in terms of how "hard" or "easy" it is to perform the task. A task difficulty can be measured in terms of error, time and some cognitive levels of "comfort" (Watson and Ntuen, 1996).

We should note that a task complexity is not necessarily the same as task difficulty. Task difficulty may or may not be a function of complexity. In the QWI (Watson and Ntuen, 1996), both concepts are used interchangeably for reasons to be explained later.

The QWI is defined by

$$QWI = \begin{cases} \dfrac{c - e^{-0.5a}}{c + e^{-a}}, & \textit{for stable systems (no oscillatons)} \\[2ex] \dfrac{c - (1/b)e^{-a}}{c + e^{-a}}, & \textit{for unstable systems} \end{cases} \quad .....(6)$$

where: **c** is an hypothetical work content or "load"; this may be a distribution of time available to complete a task; e^{-a} is energy loss to the work environment (see Gheorghe, 1979); $c + e^{-a}$ is the total system work content; and a is the complexity parameter. **a** can be defined in various ways. For our compensatory task experiment.

$$a = \frac{RMS(e)}{RMS(s)} \quad ....(7)$$

where RMS(e) is the root mean square of control error and RMS(s) is the root mean square of the task dynamicity: (s-1) for position error; (s-λ) for velocity, $(s-\lambda)^2$ for acceleration; b is the system damping coefficient, and

$0 \leq QWI \leq 1$, with the conditions:

$(c - e^{-0.5a}) > 0$, for b = 0
$c \geq (1/b)e^{-a} \geq 0$ for b > 0

No evaluations for b < 1 is available in the QWI model

4. METHOD

The Manual Control Laboratory was used in the experiment. The goal of a compensatory tracking task is typically to minimize the time-average delays between apparent task execution failures. The subjects' perceptual and control strategies are focused primarily on how to compensate for this failures. On the experiments, the subjects are required to keep a vertical bar within a reference box of defined width and length in a stationary target. Within the dynamic parameters, position control output is a direct result of the movement of the control device. The level of difficulty was introduced by varying the disturbance parameter (λ) over the amplitude of the cursor. This range from 0.0 to 1.0 half-screen heights. Higher values result in a larger effect of disturbance. The levels of difficulties are shown in Table -1.

Table 1: Levels of Task Difficulty Defined by Overall Amplitude

Level	Amplitude Setting
1	0.2
2	0.4
3	0.6
4	0.8
5	1.0

Bandwidth settings and disturbance relative amplitude in the Manual Control Laboratory (MCL) remained fixed. This was done deliberately to study only the levels of task difficulty in Table 1. The task complexities were studied at three levels: position control $\left(k/\lambda\right)$ velocity control $\left(\frac{k}{(s-\lambda)}\right)$, and acceleration control $\left(\frac{k}{(s-\lambda)^2}\right)$, $\lambda=(0, 0.5, 0.7, 0.9, 1.0, 1.5, 2.0)$ defines the instability vector induced by a gaussian type distribution with zero mean.

After performing each task, the subjects were asked to rate the task in a subjective scale of difficulty and the Cooper-Harper (1969) task handling scale. The difficulty scale used is as follows:

$0 \le D \le 1$	:	not very difficult
$1 < D \le 2$	:	slightly difficult
$2 < D \le 3$	:	moderately difficulty
$3 < D \le 4$	:	noticeable difficult
$4 < D \le 5$	:	very difficult

The Cooper-Harper (CH) task handling scale consists of opinions that are vague and imprecise on a linguistic scale of preference. An example of CH task handling scale is shown in Table 2.

The CH scale in Table-2 classifies FHQ into three levels:

Level 1: Task qualities adequate for the mission flight phase.

Level 2: Task qualities adequate to accomplish the mission flight phase, but some increase in pilot workload or degradation in mission effectiveness exists.

Level 3: Task qualities such that the airplane can be controlled safely, but pilot workload is excessive, or mission effectiveness is inadequate, or both.

Table-2: Pilot Opinion Rating on CH Scale

Characteristics	Demands on Pilot in Selected Task or Required Operation	Pilot Rating	Flying Qualities Level
Excellent; highly desirable	Pilot compensation not a factor for desired performance	1	
Good; negligible deficiencies	Pilot compensation not a factor for desired performance	2	1
Fair; mildly unpleasant deficiencies	Minimal pilot compensation required for desired performance	3	
Minor but annoying deficiencies	Desired performance requires moderate pilot compensation	4	
Moderately objectionable deficiencies	Adequate performance requires considerable pilot compensation	5	2
Very objectionable but tolerable deficiencies	Adequate performance requires considerable pilot compensation	6	
Major deficiencies	Adequate performance not attainable with maximum tolerable pilot compensation Controllability not in question	7	
Major deficiencies	Considerable pilot compensation required for control	8	3
Major deficiencies	Intense pilot compensation required to retain control	9	
Major deficiencies	Control will be lost during some portion of required operation	10	

5. A FUZZY MODEL FOR WORKLOAD ASSESSMENT

5.1 Theoretical Development

The interaction of the CH tasklevels can be represented in a linguistic geometric space as shown in Figure 1; where A is for Level 1, B for Level 2, and C for Level 3 respectively. In Figure 1, the fuzzy boundary between A and B, and between B and C represent some "occluded" interaction of cognitive opinions; and can be modeled as event interactions. Specifically, let $\mu_A(x)$, $\mu_B(x)$, and $\mu_C(x)$ represent the fuzzy membership of levels A, B, and C, the aggregate cognitive fuzzy rating is given by

function (Eshrag & Mandani, 1979).

$$\mu_S(x) = \mu_A(x) \cup \mu_C(x) - [\mu_A(x) \wedge \mu_B(x)] - [\mu_B(x) \wedge \mu_C(x)] \quad \text{.........(8)}$$

Where $\mu_s(x)$ is the fuzzy membership for describing the task rating on CH scale.

From equation (8), it is easy to show that

$$\mu_S(x) = \mu_A(x) \cup \mu_B(x) \cup \mu_C(x) - \mu_B(x)\,[\mu_A(x) \cup \mu_C(x)]$$

$$= \mu_A(x) \cup \mu_B(x) \cup \mu_C(x) - g(x) \quad \text{.............................(9)}$$

$$g(x) = \mu_B(x) \cap [\mu_A(x) \cup \mu_C(x)]$$

where g(x) is a fuzzy function describing the degree of overlapping opinions. g(x) can be obtained by using the general overlapping function (Eshrag & Mandani, 1979).

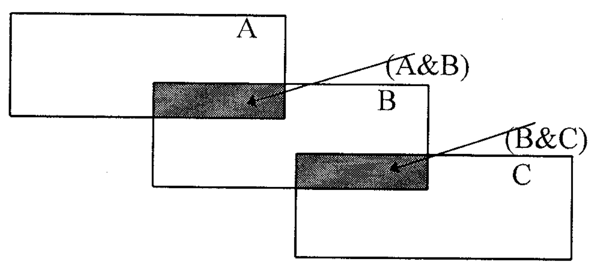

Figure 1: Set representation of FHQ levels with fuzzy boundaries.

$$\mu_{MN}(x) = \frac{\mu_M(x) \cup \mu_N(x) - \{\mu_M(x) + \mu_N(x)\}}{\mu_M(x) \wedge \mu_N(x)} \quad \text{.............(10)}$$

$$\mu_{MN}(x) \in (-1, \infty)$$

We want $\mu_{MN}(x) \in [0, 1]$, hence from equation (8), the scaled overlapping function is

$$g(x) = \begin{cases} 1/2(\mu_{MN}(x) + 1) & , \quad -1 \le \mu_{MN}(x) < 0 \\ 1 - \dfrac{1}{\mu_{MN}(x) + 1} & , \quad \mu_{MN}(x) \ge 0 \end{cases} \quad \text{...(11)}$$

5.2 Mapping Perceived Difficulty Into CH Scale

Let D be a space of point objects with a generic element of denoted by d (D is the difficulty rating). Associated with $U_D(d)$ is D= $\{(\mu_D(d_i), d_i), d_i \in D\} \to [0, 1]$.

$i = 1, 2, ..., 5$.

Equivalently, define X such that X= $\{(\mu_x(x_j), x_j), x_j \in X\} \to [0, 1]$ is the fuzzy description function of the CH scale; $j = 1, 2, ..., 10$. A fuzzy relation R on the Cartesian set N x M (N = 5, M = 10) is defined as a mapping of D onto X such that $\forall\, d_i \in D$, $\forall\, x_i \in X$, $R(d_i, x_i) \in [0, 1]$. According to Yager (1977), R is a measure of the possibility or perception of how the task difficulty contributes to task handling quality. The greater the value of $R(\cdot)$, the more difficult the task handling performance. The fuzzy distribution induced by $R\cdot(\cdot)$ is defined by

$$\mu_D(d) = \max\{\mu_R(d, x) \wedge \mu_D(d)\} \quad \text{........................(12)}$$

5.3 Experimental Fuzzy Distribution

The experimental fuzzy distribution obtained is an aggregation of subjective and objective measurement of the task workload defined in equation 6 (with c =

1). The fuzzy workload model is defined by

$$\mu_{WL}(v) = \begin{cases} \dfrac{1}{1+\exp\left\{\dfrac{-\pi v}{\sqrt{1-v^2}}\right\}}, & 0 \le v \le 1 \text{....(13)} \\ 0, & else \end{cases}$$

Where v = QWI; the denominator term is the peak of the step response of the close-loop control system (Biernson, 1988).

6. SAMPLE RESULTS

Eight graduate students (5 males and 3 females with an average of 24.3 years of age took part in the study) under the experimental conditions specified earlier. The experiment involve trials in random order to ensure that learning effects were eliminated with the aggregation of the difficulty and CH ratings based on the obtained QWI. The membership value was calculated using equation (13) and the normalized values obtained by dividing each value with the maximum rating obtained. Tables 3-5 give sample values for position, rate, and acceleration compensatory control tasks respectively. These data are displayed in Figure 2 by plotting the fuzzy membership as a function of QWI. Although we do not have sufficient data to conduct robust statistical tests, Figure 2 indicates fuzzy membership distribution by task difficult levels. This is similar to the CH levels described earlier. Figure 3 shows the average CH rating for each task level as a function of system instability.

Table 3: Workload Membership Function For Position Compensatory Task

Workload index	Calculated membership	Normalized membership
0.17	0.632	0.712
0.22	0.67	0.755
0.28	0.714	0.804
0.31	0.736	0.829
0.35	0.764	0.86
0.43	0.818	0.921
0.55	0.888	1

Table 4: Workload Membership Function For Rate Compensatory Task

Workload index	Calculated membership	Normalized membership
0.39	0.791	0.827
0.48	0.848	0.887
0.59	0.907	0.949
0.66	0.94	0.983
0.7	0.956	1

Table 5: Workload Membership Function For Acceleration Compensatory Task

Workload index	Calculated membership	Normalized membership
0.63	0.927	0.927
0.74	0.97	0.97
0.82	0.989	0.989
0.86	0.995	0.99
0.95	0.999	1

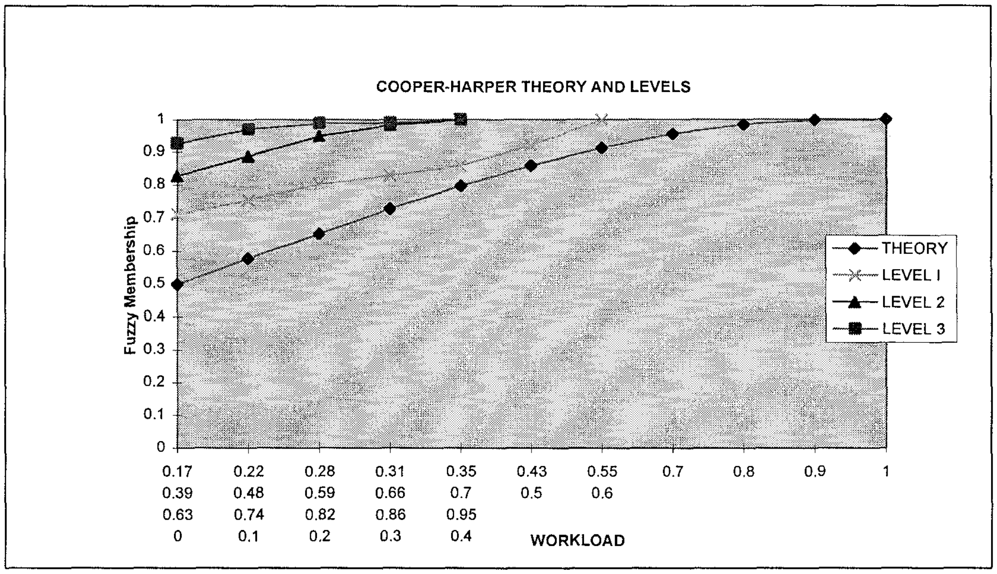

Figure 2: **Fuzzy Membership Distribution By Task Levels.**

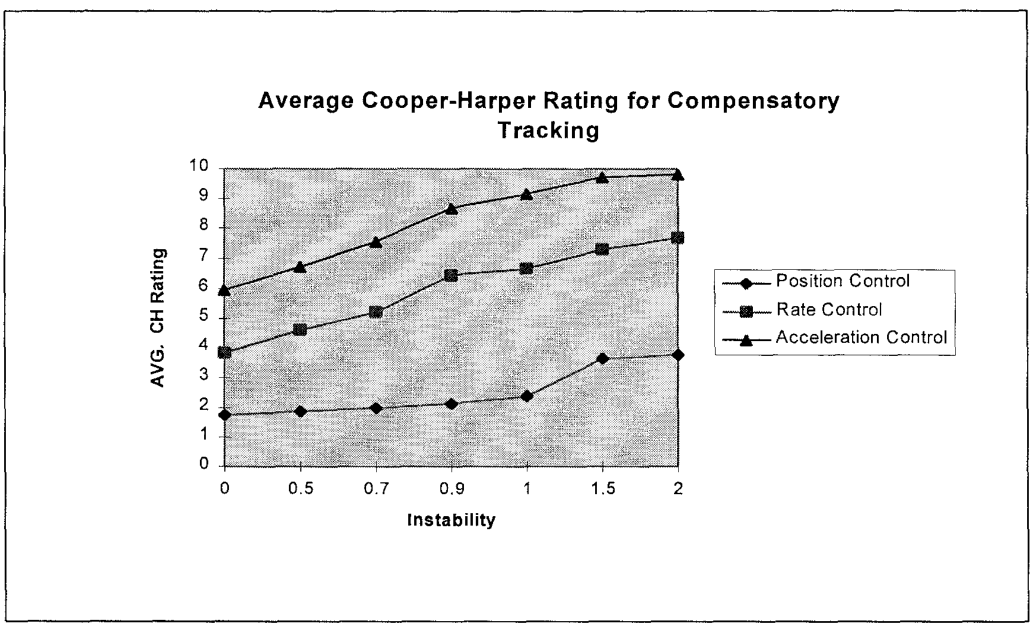

Figure 3: **Average CH rating for each task level as a function of system instability.**

7. CONCLUSIONS

This paper has presented a fuzzy model of workload as a function of task difficulty and complexity. While the fuzzy model is developed from compensatory tracking tasks, the concepts can be generalized to many situations involving the combination of subjective and experimental data. Some further studies are required. Other interests are the investigation and classification of tasks based on the CH levels as a function of task difficulty and complexity and the development of fuzzy predictive model for human performance based on the perception of these levels. Further, the investigation of effects of control bandwidths deserve some attention (see, e. g., Strickland, Ntuen, & Park, 1995; and Moray and Waterton, 1988).

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