COMPARISON OF MENTAL WORKLOAD AND AVAILABLE CAPACITY IN COMPLEX PERSON-MACHINE SYSTEMS

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ABSTRACT

A method is described for building intelligent person-system interfaces which are responsive to changes in task demand. This approach uses on-line mental workload (MNL) assessment procedures which are comprised of both physiological and performance measures. Comparison of available perceptual and cognitive capacity with the current level of MNL demanded of the operator by the task activates a compensatory procedure that shifts the processing load toward or away from the human in order to optimize overall system performance. This procedure is dependent on the derivation of the error signal which is input into the compensatory system element. The overall success of the intelligent interface relies largely on the validity and accuracy of this error signal. The error signal is based on a fuzzy set-theoretic formulation. A multivariate profile of physiological responses and measures of primary task performance are mapped onto two fuzzy sets. A fuzzy discriminating criterion, related to the fuzzy cluster-analytic model, is used in assigning the membership functions for each of two MNL categories. The resources required by the task are specified in terms of set membership functions for each attentional resource. This information is combined into an error signal used in subsequent dynamic task reallocation.

INTRODUCTION

In this chapter we present a brief view of an adaptive human-machine system and the components which constitute such an assembly. The goal of an adaptive human-machine system is to perform a defined task optimally, within the constraints of the environment and the processing resources available to the human and the machine, both singly and in combination. This goal can be achieved only if there is a cooperative relationship between the human and the machine which allows precise orchestration of the tasks performed by each of these two components of the system. In the past, such a cooperative relationship was unachievable as input to the machine was constrained by a complex command syntax which was difficult to learn, and translational interfaces were unavailable. As a result of recent technological advances, however, the development of intelligent interfaces which can support effective human-machine communication and cooperation is now possible.
A knowledge-based adaptive mechanism (KRAM) is capable of controlling the task allocation and load leveling functions within a human-machine system [2]. Load leveling is required because of fluctuations in the perceived or actual difficulty of the task over time. Figure 1 shows how the mismatch between task demands and available resources can vary over time. Load leveling is particularly important when the mismatch is sufficient to produce inadmissible overload or underload as illustrated by the shaded areas within the figure. Any KRAM which acts as a buffer, task generator or load leveler between the task and the operator, must be capable of assessing the MML imposed within a short time frame and in a sufficiently accurate fashion. Task reallocation can be accomplished through user-generated commands instructing the machine to assume control of certain tasks, or by the intervention of a KRAM system. In the latter mode, upon detection of an abnormal level of MML, the adaptive mechanism redefines and reallocates the task or subcomponents of an overall task, unless specifically directed to do otherwise by the user.

Figure 1. Schematic Representation of the Time-Varying Mismatch between Task Demands and Available Capacity.
The major purpose of the current chapter is to show how the error signal required by a KBAM system may be derived. This signal, through which subsequent task reallocation and redefinition is achieved, is produced through the combination of fuzzy set theory, attentional resource theory, and contemporary MWL assessment methods.

MENTAL WORKLOAD ASSESSMENT

There are a variety of methods by which MWL may be measured [3, 4] including 1) subjective ratings, 2) primary task performance measures, 3) dual task assessment, and 4) physiological assessment techniques.

Subjective Rating

Subjective ratings are used as a measure of the behaviorally perceived difficulty of a task. This is a potentially useful measure since the goal of a KBAM is to relieve the operator of excessive MWL, whether the overloading is objectively or subjectively defined. However, rating of perceived difficulty is itself a task and it may result in an additional loading for the operator. This is particularly true if the rating responses are required during actual performance. Furthermore, the use of subjective ratings may be confounded by variations in the motivation of the performer which are not directly related to task difficulty. In addition, it is possible that subjective reactions do not map directly to the level of performance on the primary task at hand. This dissociation [5] has important implications for the derivation of the KBAM error signal.

Attempts to improve the validity of subjective ratings have led to the use of multiple ratings and averaging techniques. These advanced methods for collecting subjective ratings are, however, inappropriate for monitoring MWL on-line as they are almost exclusively post hoc and static rather than predictive and dynamic. Also, multiple rating judgments and subsequent interpretation require information integration over relatively long periods of time. In spite of the attractiveness and face validity of subjective ratings, as currently formulated they are not well suited to continuous measurement of MWL, are somewhat intrusive into the primary task, and if and when used in a KBAM they would require supplementation by other assessment methods.

Performance Measures

Measures based on primary task performance may be the most obvious method of workload assessment. There are several methodological approaches to the measurement of performance or system output measures, and these have been discussed by Chiles and Alluisi [6]. Welford's [7] concept of the analytical approach focuses on details of the performance of the task itself and examines
not only overall achievement but also the way in which the task goals are attained. The advantage of this particular method is that the various decisions and responses that make up performance are considered in the context in which they normally occur. As a result the full complexities of any interaction between different elements in the task may be observed. This approach requires that several performance scores are taken of repetitive performance events, and consequently this analytical approach requires extensive data collection.

Welford [7] has suggested that the analytical approach allows the more subtle effects of workload to be examined by making transparent the strategies employed by the individual performer. Examples of analyses which might be made include assessment of the tradeoff between speed and accuracy, and between errors of omission and commission, and methods of operation which in various ways seek to increase efficiency and to reduce excessive load. The approach has two major problems. First, that the detailed scores required can be difficult to obtain for tasks such as process monitoring in which most of the decisions which are made do not result in any overt action. Second, that even where there are sufficient observable actions, recordings are often elaborate and analysis of results laborious. Consequently, its use in real-time systems is problematic and awaits methodological refinement at the present time.

Synthetic methods require a task analysis of the system which divides the overall task into operational phases. Performance times and operator reliabilities are assigned to the individual tasks and sub-tasks on the basis of the availability of derived data. The information on performance times is then accumulated and the total compared with the predicted duration of the task. The ratio of time required to time predicted can be employed as an index of workload. This approach is similar to the calculation of standard times in work measurement, where performance rating is used to adjust for the effects of skill and motivation in assessing task-related workload on the basis of performance measures [8].

MWL assessment through performance analysis is also possible using multiple measures of primary task performance. This has the beneficial effect of reducing the likelihood that important strategy changes will go unnoticed [3]. One area of concern, however, is that individual measures are differentially sensitive to the various aspects of the task, which may make scaling of workload difficult for specific tasks. Performance measures typically are integrated over time and are often incapable of reflecting sudden changes in MWL and consequently do not provide a satisfactory predictive capability. It has been argued [3] that the measures of primary task performance are task specific. Each time a new situation is examined, new measures must be developed and tested. In many situations, increasing workload
may have little effect on performance as the operator has sufficient reserve capability to adapt to the increased load. Performance may not drop off appreciably until a point of critical overload is reached [9] by which time compensatory actions may be too late to recapture or recover a stable performance state.

Secondary Task Methods

Secondary task measures are based upon the rationale that the human operator has only a limited amount of resources to devote to one or more tasks. It is assumed that the imposition of a second task in addition to the major or primary task can reach or potentially exceed an operator's capacity. The MWL of the primary task is then calculated as being inversely proportional to the level of secondary task performance. This method suffers from a number of problems, such as individual load shedding strategies, impingement of one task on the other, and competition between the tasks for access to a single sensory or output channel.

Recently, secondary task methods of MWL assessment have assumed a multiple resource model of attentional capacity [10]. In this view, separate resource pools are used for different aspects of the task. Initially, it was postulated that these pools were functionally separated and could, in principle, become completely drained. Later experimental results have implied that task integrity may sometimes occur, with the addition of an extra task improving, rather than hurting performance on the tasks already being performed, even though the new task is addressing the same resource pool as the previous tasks [11]. The existence of task integrity makes the use of secondary task methodology even more problematic with respect to workload measurement.

Although secondary task methods have been used to measure MWL in the laboratory, they appear to be unsuited for application in realistic complex work environments which typically consist of more than two tasks, often with a high loading on attentional resources. In such environments it is often infeasible to add a further task purely for MWL assessment purposes. It should also be noted that the use of one or more tasks to indirectly assess MWL as a performance decrement conflicts with the major goal of a CRM, which is to optimize the overall performance of a person-machine system.

Physiological Measures of Mental Workload

Since individuals who are subjected to some degree of MWL commonly exhibit changes in a variety of physiological functions, researchers have advocated the measurement of these changes to provide an estimate of the level of MWL experienced [12, 13]. In dealing with physiological measures we should recognize that many aspects of operator behavior other than MWL can have an
effect on the physiological measures [14]. In order to reduce the confounding
effects of extraneous factors such as emotional responses which will impact on
some measures more than others, a multivariate model is required for relating
profiles of physiological response to level of MWL. To the extent that such a
model can only be approximate, and levels of MWL can not be identified with
complete accuracy, the problem becomes one of fuzzy classification on the basis of
noisy multivariate data. Before considering a fuzzy set-theoretic
formulation of this problem however, we shall summarize the types of
physiological measures which may be appropriate and the ways in which they may
be related to MWL.

The interaction between the individual and the environment is reflected in
physiological response. As MWL presumably affects the activity of the CNS,
measures may variously reflect processes such as demand for increased energy,
progressive degradation of the system or homeostatic action of mechanisms
designed to restore system equilibrium disturbed by the requirements of
cognitive tasks. Currently available physiological measures appear to be
similar in some respects to subjective ratings in that they reflect a
subjective physiological response to task difficulty. As Ursin and Ursin [12]
suggested, physiological methods do not measure the imposed load directly, but
instead give information concerning how the individuals themselves estimate the
load and their ability to cope with it. Thus physiological measures appear to
reflect a subjective response to the task, in the form of perceived task
difficulty and anxiety associated with that perceived difficulty. The great
advantage that physiological measures have over other methods is that they can
be measured continuously and, with careful application, they are not intrusive
with respect to performance on the primary task. Furthermore, to the extent
that perceived loading is predictive of performance breakdown, the individual’s
perception of the workload may be precisely the criterion required for task
reallocation using a KBAM.

THE MISMATCH BETWEEN TASK DEMANDS AND AVAILABLE RESOURCES

Physiological measures appear to be the most useful form of MWL assessment
for a KBAM system. Not only do they supply a continuous stream of data which
is amenable to statistical analysis, but they also reflect the human’s
physiological perception of the current workload and they do not alter the
existing task structure substantively. Performance measures also provide
important clues about the operator’s ability to perform the task as currently
defined. The problem of converting a matrix of physiological and performance
measures into a signal which provides the necessary information for task
redefinition and reallocation within a KBAM can only be solved if a complete
specification of the information required by the KBAM is given. The
informational requirements of a KBAM result from its purpose, which is to optimize system performance, and from the processes used to achieve that purpose.

In order to maintain satisfactory levels of both MML and system performance, a KBAM assesses the mismatch between task demands and available capacity and redefines the task in order to reduce the detected mismatch. The input to the KBAM is an error signal representing the mismatch between current task demands and the available capacity of the human operator (Figure 2).

![Figure 2. The Formation of an Error Signal as the Mismatch between Current Demands and Available Capacity.](image)

The key component of the KBAM is a reasoning process which selects a task allocation policy that changes the loading on the human in such a way as to improve overall system performance. This process must have access to both overall system goals (a model of the task) and information about what the person and machine components of the system are capable of accomplishing (person and system models). In addition, it is required to decide which loading strategies and task allocation policies are available for selection, and what the implications of the current error signal(s) are.

We can use a process of elimination to determine what information should be supplied by the error signal. Models of the task, person, system, and available loading strategies are already available in the other inputs to the
loading strategy reasoner, but none of these inputs give information about the current status of the person. Thus the error signal is a dynamically changing input which has to be combined with the static information provided by the other informational sources available to the loading strategy reasoner.

Not only must the error signal provide information about how well the person is performing particular subtasks, but it must also indicate any discrepancies between overall system performance and system goals in order that the available capacity of the person can be integrated with the needs of the entire system. It would be inappropriate to optimize the workload experienced by the operator if the overall system failed or suffered as a consequence. In this chapter we focus on the component of the error signal which provides information about the status of the human operator. This information will include the amount and direction of MWL (whether increasing or decreasing) experienced by the human.

MWL indicates the direction in which task-induced loading on the person should be altered, but not how the task loading should be achieved. An error signal that was based solely on MWL and performance measures would not provide information about the particular aspects of the person's task or subtasks that were producing over- or under-loading. Thus the input to a KWM load leveling system also needs to provide a third type of information, namely the extent to which different aspects of the task are using up available resources. We shall now consider the types of resource that are available to the person before considering the error signal in fuzzy set-theoretic terms.

**ATTENTIONAL RESOURCES**

Early research demonstrated that auditory processing depends on limited resources [15, 16, 17]. More recent research has found that a concept of capacity as a single and global resource which can be allocated to all tasks [18] is insufficient to explain the relationship between task difficulty and human performance. Some tasks will be difficult because they require a lot of resources in general, while other tasks may have components which interfere with each other. Tracking, recognition, and decision making tasks have been used to identify the functional relationship between multiple resources and input/output limitations of the human operator [19].

The interference between tasks can be of two types, which are referred to as structural limitation and structural interference. Structural limitation occurs in situations for which dual-task performance deteriorates as a result of the physical constraints on the processing system. Thus, the eye cannot view two separated locations at once, the mouth utter two words at once, nor a specific limb be in two places at the one time. The concept of structural interference can account for such instances as the difficulty in simultaneously performing two independent motor acts such as rubbing the head and patting the
stomach. In this example, excessive demands are made upon the processing resource responsible for response output. Although also related to the similarity of demands on the motor system, structural interference is not due to the physical constraints of the limbs and therefore such limitation may be overcome with practice. Instead, structural interference is a curtailment of central nervous system capacity responsible for conjoint action of sensors and/or effectors.

Wickens [19] suggested a three-dimensional model of resources where the dimensions were defined by stages of processing (perceptual-central versus response), codes of perceptual and central processing (verbal versus spatial), modalities of input (visual versus auditory), and response (manual versus vocal). This model has proved useful in accounting for empirical results. It is the foundation of considerable applied research in areas such as the design and operation of complex systems and is used in the error signal definition below.

A FUZZY ERROR SIGNAL

As discussed above, the error signal which is input to a HBM should have two major components, one dealing with the induced workload and resources utilized by the human, the other more system-related, dealing with the discrepancy between system goals and performance, and the extent to which different aspects of the task are using up the resources available to the system. The formulation of the first (human) component of the error signal based on a fuzzy subset mapping will now be outlined.

Mental Workload

A fuzzy subset A of a universe of discourse U is defined by a membership function:

\[ f_A : U \rightarrow [0,1] \] (1)

which associates with each element u of U a number \( f_A(u) \) in the interval \([0,1]\), where \( f_A(u) \) represents the grade of membership of u in A [20]. For the purposes of MWL assessment, let the universe of discourse \( M \), say, be a vector comprised of a concatenation of physiological and performance measures. The inclusion of performance measures makes the MWL estimate more task specific, since tasks will differ markedly in terms of the MWL implications of different levels of performance. The selection of physiological measures to be monitored will be based on the practicality of the required measurement method (in terms of cost, intrusiveness and reliability) and the strength of the arguments (presumed causal connections) relating the measure to task-related CNS activities.
In developing a unitary measure of MMWL on the basis of a set of physiological and performance measures we will adopt a method suggested by Mital and Karwowski [21]. Let us define two fuzzy subsets labeled "excessive mental workload" and "insufficient mental workload" respectively. We then have two corresponding membership functions, \( m_{EMWL} \) and \( m_{IMWL} \) which map the vector \( M \) of physiological and performance measures into the two fuzzy subsets. The membership function \( m_{EMWL} \) for instance, associates with each measure \( M_i \) in \( M \) a number \( m_{EMWL}(i) \) in the interval \([0,1]\) which represents the grade of membership of \( M_i \) in the fuzzy subset "excessive mental workload". The closer this number is to 1, the stronger the indication that the individual is under excessive mental workload. The numbers \( m(M_1), m(M_2), \ldots \) can be assigned for each of the measures in \( M \) and this vector of membership functions (corresponding to the original vector of measures) can then be condensed into an overall estimate of the degree of excessive MMWL present. One method of combining the measures is to use a weighted average, thereby allowing for differences in the relative importance of each measure. It is suggested [21] that expert opinion be used to derive these weightings, but we consider an empirically-based approach for obtaining appropriate weightings in the example below. We have chosen to use two fuzzy subsets to assess MMWL, rather than one, to allow for more sensitivity in measurement. In process control tasks, for instance, where long periods of insufficient MMWL may be interspersed with short bursts of excessive MMWL, it may be reasonable to assess separately the two extremes of MMWL level, rather than to combine them on a single scale (fuzzy subset). As an example, one might have two situations both representing .5 membership in the fuzzy subset "high mental workload". In the first situation, the .5 represents an averaged response to excessive MMWL followed closely by insufficient MMWL. The second situation represents a case of a constant and fairly high MMWL. Clearly, a KBMM would need to be able to distinguish between these two situations when making corrective responses.

Resources Required by the Task

Mental Workload is experienced in response to the stress imposed by the task. Using the multiple resource view of Wickens [10] we can describe a task in terms of the resources that it requires for adequate performance. At present, we do not have adequate methods for assessing the resource requirements of tasks. One can, however, use expert opinion, possibly supplemented with experimental analyses, to estimate the resource requirements of a task.

Using similar notation to that given in the previous section, we can define a vector \( R \) of resource requirements \( R_j \) which is mapped onto a fuzzy subset labeled "excessive resource requirements". The components of \( R \) are obtained using the classification outlined by Wickens [19]. The union of these resource
requirements, i.e., \( \text{MAX}_i (R_i) \), defines a second global measure of HAWL which should covary with the estimate based on the vector \( M \) of physiological and performance measures.

**Spare Resource Capacity**

The resources required by a task can be represented as a vector \( R \), as described above. A similar vector \( U \) showing the utilization of these same resources can be constructed. In a given situation, this vector would be specified by instantiated membership functions for each of the relevant resource components (which would include functions for visual input, auditory input, spatial code, verbal code, encoding, central processing, manual response, and vocal response) into the fuzzy subset "complete resource utilization". In practice, however, it is easier to measure spare capacity using probe secondary tasks and similar techniques than it is to measure resource utilization directly.

![Diagram](image)

**Figure 3. Hypothetical Relationship between Requirements for, and Utilization of, Human Attentional Resources.**
In manufacturing engineering, production planning is based on the availability of different resources. In any system, a certain amount of spare resource capacity should be available at all times in case of unexpected breakdowns or increases in demand [22]. Figure 3 gives a schematic view of the relationship between task demands and resources supplied, and the resulting effect on task performance. To the extent that spare resource capacity indicates whether task demands can be met by current resources it serves as a predictor of performance. It is the job of a task allocation process to ensure that, under all but emergency conditions, sufficient amounts of spare capacity are available for all the task-relevant resources.

The tasks performed by the system define the implied resource requirements vector $R$ as described above. Using probe task techniques it should then be possible to identify an additional vector $C$ specifying the degrees of membership for each of the resource components in the fuzzy subset "full resource capacity available."

Given the vector $C$, the vector $U$ corresponding to utilization of resources can be estimated as the inverse of the spare capacity membership functions, i.e.,

$$V_1U_1 = 1 - C_1$$

Global measures of $MWL$ tell a KBAM system what change in $MWL$ level is needed, but not how to implement that change. The current mismatch between resources required by the task and resources utilized by the operator will provide the information needed to implement a more favorable set of task requirements. Thus the vector difference between $R$, the resource requirement vector, and $U$, the resource utilization vector, defines $A$, the vector on which task reallocation is to be made, i.e.,

$$A = [(R_1 - U_1), (R_2 - U_2), \ldots]$$

The size of this mismatch, $R_{deviation}$ can be derived as the Hamming distance between the vectors $R$ and $C$, i.e.,

$$R_{deviation} = \sum_i [ABS (R_i - C_i)]$$

$R_{deviation}$ can be used as a third estimate of global $MWL$.

Overview of the Error Signal
The purpose of the error signal is to provide dynamically changing information about the human operator both in terms of overall $MWL$ being
experienced and mismatches between resource requirements and resources utilized. The utilization of this error signal in task allocation is then a two-stage process. First, a global assessment of MNL is made, i.e., is MNL too high or too low and by how much? Second, the resource mismatch vector is used to implement a task reallocation policy designed to return the operator to a more desirable level of MNL. Although the fuzzy logic formalism for combining the various membership functions into an error signal is straightforward, the problem of how to derive membership functions and associated numbers in the first place is not. It is likely that existing techniques of work measurement and task analysis can be extended to provide estimates of the vector R. It is also likely that a variety of methods, including evoked potential measurement (the P300 component in particular), analysis of eye movement patterns, and the like will lead to reasonable estimates of resource utilization. It is assumed here that the scaling of physiological and performance measures as membership functions on the fuzzy subsets "excessive mental workload" and "insufficient mental workload" will be based on experimental functions derived from existing experimental data. The final measurement problem consists of assigning membership functions in the fuzzy subsets "excessive mental workload" and "insufficient mental workload" on the basis of the vector M. This problem is considered from a fuzzy classification perspective in the next section.

Fuzzy Classification

The KBAM method of adaptive control requires a fuzzy error signal that includes the information on MNL and performance which is vital for task rescheduling and reallocation. As defined earlier, the fuzzy error signal will consist of three global measures of MNL, the first based on a weighted average of M, the second based on the maximum resource requirement (Max P_i) of the task and the third based on the measure R_deviation defined above. The error signal will also include the vector λ, specifying the difference between requirements and utilization for each type of human attentional resource. The problem of deriving the first global measure of MNL on the basis of multivariate profiles of physiological and task performance measures is one of fuzzy classification. Methods for making this classification will now be considered.

If the categories are well defined a priori, one can use a discriminating function to allocate a given profile to a particular category. This procedure assumes that the categories can be represented as a partitioning of the space of multivariate profiles. In fuzzy classification, profiles are not exclusively inside or outside a single category, but have grades of membership in one or more categories. Since appropriate discriminating functions for MNL scaling on the basis of physiological and performance measure are currently
unavailable, techniques which require fewer a priori assumptions will now be considered.

Cluster analysis is a second type of classification which assumes no prior information about the categories to be formed. It is essentially an unsupervised pattern recognition technique [23] which uses measures of similarity or distance between the profiles to develop a classification solely on the basis of the data input [24]. While this method is appealing because it requires no prior assumptions about the categories to be formed, it is difficult to assess the validity of the obtained clusters [25]. Since cluster validity is difficulty to assess, an unsupervised technique such as fuzzy cluster analysis will not be appropriate for assigning MNL because one cannot ensure that MNL, rather than another criterion, such as motivation or fatigue, is being used as the basis for classification.

A third method of classification uses supervised training [23]. Calibration of MNL can be achieved using the following supervised training method. MNL and performance are observed under a wide range of conditions, with global MNL being assigned as grade of membership in the fuzzy subsets "excessive MNL" and "insufficient MNL" on the basis of subjective ratings by the person doing the task and ratings made by the experimenter on the basis of observation and task analysis. A large collection of these observations, with the associated fuzzy classifications, would then form a training sample. New samples could then be classified without further rating of global MNL using a nearest neighbor allocation rule. Each new profile would be matched against the training sample. It would then be assigned the fuzzy classification given to the most similar profile in the training sample. Euclidean distance could be used in assessing the nearness of profiles, although a number of other measures are available [26].

**ERROR SIGNAL DERIVATION: AN EXAMPLE**

The derivation of the error signal begins with the acquisition of the data required for the vectors M, R, and C. Table 1 shows a set of hypothetical data along with associated measures of global MNL (\(M_{RNL} \), \(R_{Max} \), \(R_{deviation} \)) and the resource requirements-utilization mismatch (A). The weighted average of M using an arbitrary vector of weights (W) is .39. This is then normalized by multiplying the obtained average by the number of weights used divided by their sum. In this example, the normalized weighted average is .65, which is the same as the unweighted average. It remains to be seen whether the additional effort of weighting is justified by the increased sensitivity of the M_{RNL} measure. If an appropriate training sample were available, nearest neighbour allocation could be used instead of the weighted average approach, as outlined in the previous section, to derive an estimate of M_{RNL}.
\[ M = [0.7, 0.5, 0.6, 0.8, 0.9, 0.4] \]
\[ W = [0.8, 0.8, 0.4, 0.3, 0.8, 0.5] \]
\[ R = [0.9, 0.1, 0.5, 0.8, 0.8, 0.7, 0.9, 0.1] \]
\[ U = [0.9, 0.3, 0.4, 0.9, 0.8, 0.6, 0.7, 0.3] \]

\[ M_{ENWL} = 0.39 \times 6/3.6 = 0.65 \]
\[ R_{Max} = 0.9 \]
\[ R_{deviation} = 0.9 \]
\[ A = [0, -0.2, 0.1, -0.1, 0, 0.1, 0.2, -0.2] \]

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**TABLE 1**

Hypothetical data to illustrate the error signal derivation method. The four physiological measures \( M_1 \rightarrow M_4 \) are auditory canal temperature, heart rate variability, blood pressure, and galvanic skin response (GSR), respectively. \( M_5 \) and \( M_6 \) are measures reflecting the speed, and accuracy, of task performance. \( W \) is a vector of weightings assigned to each of the components of \( M \). For the purposes of this example we only consider the subset "excessive mental workload." A separate vector of weights would be required for the fuzzy subset "insufficient mental workload." The resources used in \( R \) and \( U \) are ordered as follows. 1 = visual input, 2 = auditory input, 3 = spatial code, 4 = verbal code, 5 = encoding, 6 = central processing, 7 = manual output, 8 = vocal output. This data was generated on the basis of a conceptual analysis of the same-different matching task [27].

Thus the nearest \( M_j \) in the training sample might be \([0.7, 0.4, 0.7, 0.8, 0.9, 0.3]\) with an associated \( M_{ENWL} \) rating of 0.7. The rating of 0.7 assigned to the nearest neighbor in the training sample could then be used as the estimate of \( M_{ENWL} \) for the current \( M \) vector.

\( R_{Max} \) is 0.9, reflecting the high resource requirements for visual input and manual output which is characteristic of the matching task considered in this.
example, $R_{\text{deviation}}$ is .9 (out of a maximum value of 8.0) indicating that resource utilization matches resource requirements fairly closely, despite the high level of MNL implied by the first two global measures. The vector $A$ implies desirable changes in the requirements for each resource. In the example, inspection of $A$ indicates that it might be desirable to decrease the requirement for manual output, while small increases in the requirements for auditory input and vocal output should be possible without adverse effect on global MNL.

SUMMARY

In order to produce systems that take greatest advantage of the unique capabilities of humans and machines and to provide such systems with the facility to operate in real time in work environments where demands change frequently, it is necessary to extract information on how hard the human operator is working. As a biological entity, the human is not amenable to several of the techniques which can be applied to the assessment of machine workload. The lack of physical activity, with concomitant increase in cognitive activity, further compounds the difficulty of the measurement problem in many tasks [13].

The derivation of a valid error signal, especially in relation to the limits of the human operator in general, and specific operators in particular, is the major barrier to the implementation of knowledge-based adaptive mechanisms. In the present chapter we advocate the use of fuzzy set-theoretic measures to assess human MNL and the resource requirements-utilization mismatch. This has the advantage of providing specific information concerning what is, at present, an indeterminate phenomenon, and allows the use of fuzzy classification techniques to synthesize the major forms of current MNL information into a viable error signal. Implementation of this procedure is the subject of current investigation.

The assessment of MNL and the derivation of an error signal for a KBAM is well suited to the fuzzy set-theoretic approach. It would be precipitate, however, to implement an associated calculus of operations such as fuzzy set union and set intersection at this time. Instead, we have developed the rationale for a fuzzy error signal in the KBAM methodology based on simple averaging, differencing and rating techniques. Since there is uncertainty over both the assessment of MNL and its incorporation within the error signal we have a case of uncertainty squared where calibration based on careful experimental work is required. An alternative view on fuzzy controllers is given in the work of Manclani [28]. We prefer the fuzzy classification approach to alternative methods which use concatenation of fuzzy set operators because fuzzy classification assumes less about the ways in which physiological
responses and performance measures interact both with each other and amongst themselves.

For the current functioning of complex systems we continue to rely upon the adaptability of the humans and their unique and often poorly specified capabilities. Trends toward rigidity and complexity (e.g., increase in system degrees of freedom) in system structure no longer permit the inclusion of such a poorly understood and unquantified component. While automation has had a major impact on the workplace, it cannot yet replace those unique capabilities of the human which are not as yet implementable in terms of computational models. This chapter presents an approach to the instantiation of cooperative action, in which adaptation is now a machine function. It is our view that such adaptive action is not only desirable, but with current developments, vital to continued harmonious human-machine interaction. While initial application is directed toward systems which operate at the extremes of performance, we view the development of intelligent interfaces in general, and knowledge-based adaptive mechanisms in particular as central issues in the Human Factors endeavor.

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