Deterministically Nonlinear Dynamical Classification of Cognitive Workload

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Abstract

Understanding and monitoring the changes in the cognitive workload of trainees can offer critical quantitative information about their progression and performance. Unfortunately, accurate real-time objective quantification of cognitive workload has, thus far, proven elusive and is often neglected in favor of subjective self-reports. This paper reports a novel technique for the classification of cognitive workload using methods from the domain of deterministically nonlinear dynamical systems. The reported technique utilizes physiological input data, specifically the subject's electrocardiographic (ECG) signal, captured during task performance. The novelty of the proposed algorithm stems from its ability to perform real-time, as well as after-action review, classification of cognitive workload using the full ECG signal. As will be presented, the use of the full ECG signal offers the ability to determine even small changes in the subject's workload and proves itself far more accurate than the standard classification methodology using heart rate variability (HRV). Further, the proposed methodology offers the ability to create accurate, real-time workload metrics over diverse populations and tasks; thus, reducing the need for individualized model creation. The proposed algorithm is validated through a case study in which participants were asked to perform varying levels of the Multi-Attribute Task Battery (MATB) developed by NASA. The case study punctuates the high accuracy of the proposed algorithm and its ability to classify cognitive workload levels in real-time and after-action review.

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INTRODUCTION

Understanding and monitoring the changes in the cognitive workload of trainees can offer critical quantitative information about their progression and performance. Unfortunately, accurate real-time objective quantification of cognitive workload has, thus far, proven elusive and is often neglected in favor of subjective self-reports. However, the determination of workload in participants, while performing specific tasks, has been a topic of much interest over the past few decades. This interest has been heightened by many recent application needs, including determining the fidelity of simulators (Davidovitch, Parush, & Shtub, 2009; Schnell, Hamel, Postnikov, & McClean, 2011; Schnell, Postnikov, & Hamel, 2011), the types of automobile user interfaces that should be incorporated to reduce workload (Pala et al., 2011; Wu, Rakheja, & Boileau, 1998), and the selection of suitable operators for unmanned aerial systems (UAS) (McKinley, MacIntyre, & Funke, 2011).

While subjective self-report measures of workload have been popular, a goal of objective measurement has been long sought in the domain. Objective measurement of workload involves the collection of various types of data from sensors on, or about, the subject and their environment. This general classification may be broken down into three sub-classes, namely process input based measures, performance based measures, and physiological based measures (Wierwille & Eggemeier, 1993). Process input based measures include metrics that are directly controlled by the subject such as steering wheel position in an automobile or flight control position in an airplane. Performance based measures include such metrics as lateral lane position of an automobile on the highway or flight technical errors based on the aircraft state (Eggemeier & Wilson, 1991). Physiological based measures include signals from sources such as electroencephalograph (EEG), ECG, eye tracking, respiration, and galvanic skin response (Schnell, Keller, & Poolman, 2008).

Input and performance based measures of workload are highly quantitative and have produced some satisfactory workload classification results in the past (Eggemeier & Wilson, 1991. For example, such measures can characterize a participant's effort expended versus the performance achieved. However, these measures do not account for cognitive workload expenditures or remaining cognitive capacity and are most often specific to the task that is being performed. Therefore, these measures are not extensible across different crew station platforms or task domains and new measures must be generated for each crew station or task. Additionally, performance based measures are at best surrogates for more direct measures of workload, such as physiological deviations from a baseline.

This paper reports a novel technique for the classification of cognitive workload using methods from the domain of deterministically nonlinear dynamical systems. The reported technique utilizes physiological input data, specifically the subject's electrocardiographic (ECG) signal, captured during task performance. Physiological measurements of workload have been attempted using EEG signals (Berka et al., 2004; Schnell, Becklinger, & Ellis, 2010; Schnell, Macuda, Poolman, & Keller, 2006) as inputs to the detection algorithms. While some of these methods have experienced satisfactory response, the obtrusiveness of the EEG sensors makes them less than optimal for real-time collection, especially during experiments of long duration. Additionally, EEG signals do not lend themselves well to population-based models but rather generally require personalized workload prediction models.

The use of EEG signals for classification of workload is well represented in the literature, two examples of which are presented here. Wilson and Russell (Wilson & Russell, 2003) attempted to classify workload using a combination of sensors, including six channels of brain electrical activity, eye, heart, and respiration measures. They were able to achieve classification accuracies around 82%; however, their tasks consisted of only two variants of the same test. Additionally, the high number of sensors used to collect the data is sub-optimal for many scenarios including in flight measurements. Matthews *et al* (2008) used a wireless EEG sensor helmet to classify workload in real-time. They achieve classification accuracies on an average of 80.5%.

Several accounts of the use of ECG in relation to workload are found in the literature. Dussault, Jouanin, Ohillippe, & Guezennec (2005) studied the changes to ECG during operation of a simulator to determine if the signals reflected mental workload. They were able to detect slight differences between novice and experts. Kamada, Miyake, Kumashiro, Monou & Inoue (1992) reported a study of the power spectrum of Heart Rate Variability (HRV) in subjects under mental workload. In that work, the authors were able to produce a classification of the subjects into two types using the ECG signal and HRV analysis.

Largely absent from the literature is an account of accurate classification of workload based solely on the ECG signal. This paper attempts to fill that void through the presentation of a classification algorithm which utilizes the chaotic nature of the ECG signal to accurately classify workload. A case study in which five subjects performed four levels of a given task each day for three days is presented, largely as proof of concept for the proposed classification methodology. In that study, the first day's data is used to generate the model and the remaining two days are classified against that model. Reported is a detailed description of the algorithm as well as the results of the case study.

CHAOTIC PHYSIOLOGY CLASSIFICATION

The research community has known for a number of years that human physiological signals in general, and ECG specifically, are deterministically nonlinear (also known as chaotic) systems (Govindan, Narayanan, & Gopinathan, 1998; Kozma & Freeman, 2002; Owis, Abou-Zied, Youssef, & Kadah, 2002). Chaotic systems are often not well represented via the normal scalar time series. Instead, the dynamics of the system are obfuscated in the single dimension whereas they become apparent when a transform of the data is made. This transform moves the data from the single dimensional scalar space into a multi-dimensional embedded phase space (Richter & Schreiber, 1998).

In the early 1980s Takens proposed a methodology for transforming scalar signals into multidimensional phase space for the purpose of observing the dynamics (strange attractor) of the system (Takens, 1980). Takens stated that the scalar signal could be transformed through an embedding process which mapped the time series data into a vector space through a time delay parameter. Given a time series data set $X = \{x_0,\ x_1, \ldots, x_n\}$, Takens suggested a transform through the use of a delay parameter τ such that the set X is transformed into a set $\boldsymbol{X}' = \{\vec{\boldsymbol{x}}_0,\ \vec{\boldsymbol{x}}_1, \ldots, \vec{\boldsymbol{x}}_n\}$ where $\vec{\boldsymbol{x}_i} = \left\{x_{i-(d-1)\tau}, x_{i-(d-2)\tau}, \ldots, x_{i+(d-d)\tau}\right\}$ and d is the dimension of the phase space. Two parameters must be calculated to use Takens delay embedding – the time delay and the embedding dimension. The calculation of the time delay parameter is often performed using the Mutual Information method discussed at length in (Kim, Eykholt, & Salas, 1999) and (Fraser & Swinney, 1986) while the embedding dimension is most often calculated using the False Nearest Neighbors method (Kennel, Brown, & Abarbanel, 1992).

The transformation to phase space using the mutual information and false nearest neighbor techniques can be illustrated nicely with an ECG signal. The panel on the left of Figure 1 depicts a portion of an ECG signal from one of the subjects of the case study discussed later in this paper. After calculating the parameters as described above, the phase space can be generated with time delay $\tau = 8$ and embedding dimension $d = 3$. The panel on the right of Figure 1 shows the phase space that is generated from the signal using the methods described above. The image of the phase space does not necessarily elicit new knowledge about the ECG signal in and of itself. However, as will be seen, the phase space offers the possibilities for greater classification accuracies than have been reported in the literature.

Chaotic systems exhibit sensitive dependence upon initial conditions. Thus, nearby orbits of the attractor, about the phase space, diverge exponentially (Lai & Winslow, 1994). This results in an amplification of uncertainties within the system. However, the chaotic system will exhibit an ergodicity about the phase space. All of this conspires to create an impossible environment for accurate long term prediction, and, unfortunately, a difficult environment for accurate classification. To facilitate an environment conducive to accurate classification the chaotic phase space is course grained into discrete states rather than maintaining the exact trajectories.

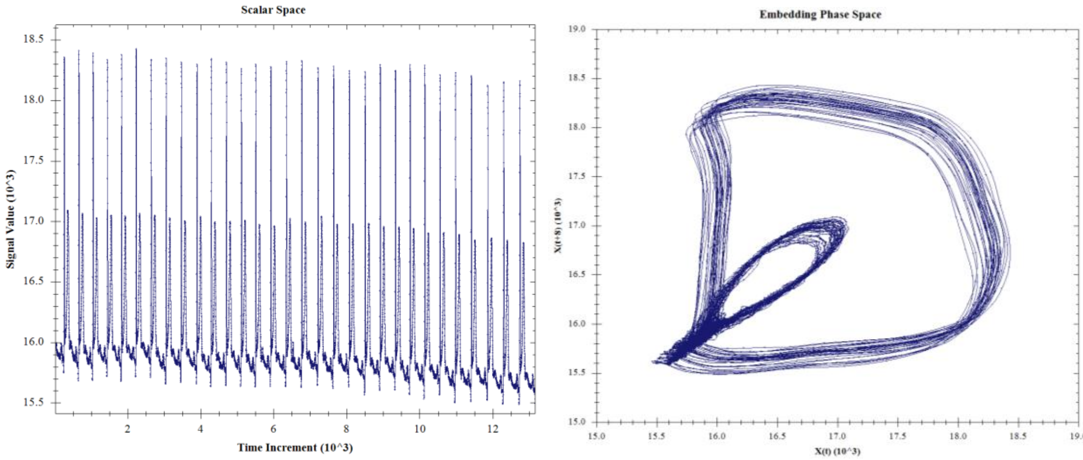

Figure 1. Example of a Scalar ECG (left) Transformed into Embedding Phase Space (right).

Flowing from symbolic dynamics, it is possible that a dynamical system $f : \Psi \rightarrow \Psi$ can have many course grained representations, each obtained by partitioning the phase space Ψ into a finite number of sets (Crutchfield & Packard, 1982). Let Ψ be the time-delay embedding phase space of a chaotic system, *S*, with time-delay τ and embedding dimension *d*. Due to the chaotic nature of *S* there exist an inherent ergodicity of *S* over Ψ. As such, orbits are formed in a quasi-periodic fashion in *S*, which are used in the proposed classification. Let *E* be an *n*-dimensional hypercube which contains Ψ, as well as other points not necessarily in the system *S*. Thus, *E* forms the *bounding space* of Ψ. Then, we can impose on *E* a, possibly fractal, partition *P* and map the points $e_{i_1,i_2,\ldots,i_n} \in E$ (where i_j is the j^{th} cell of the i^{th} dimension of the hypercube) to the centroid of the cell $p_{i_1,i_2,\ldots,i_n} \in P$ which contains the point $e_{i_1,i_2,\ldots,i_n}$. The *n*-dimensional hypercube *E* contains the course grained representation of the chaotic system. Figure 2 illustrates this course grained representation for the phase space given in Figure 1 using a partition size of *N* = 30, or 30 by 30 cells.

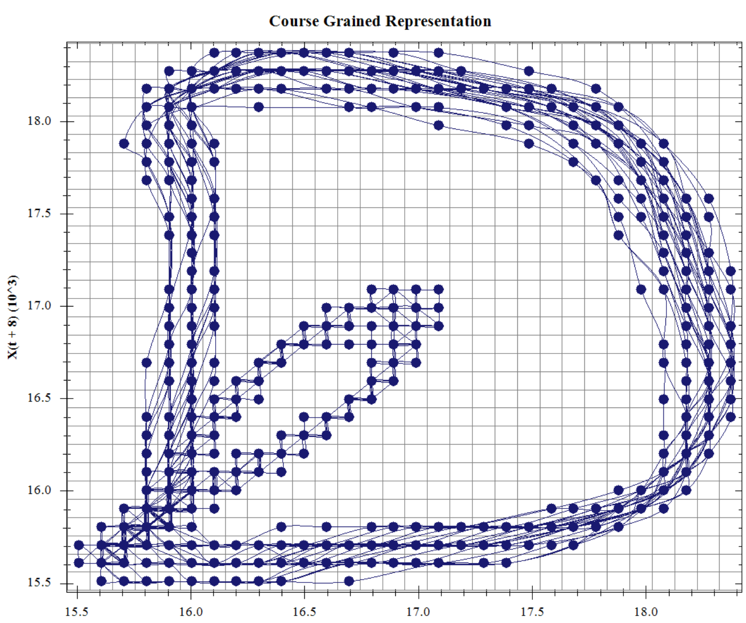

Figure 2. Course grained representation of the phase space given in Figure 1. Partition size is 30 by 30.

The partition, P, imposed on the bounding space is useful for the creation of a sparse matrix of transitions of the orbits of the system in phase space. From P, we can form a 2 dimensional matrix M of size $\prod_{k=1}^{n} i_k \times \prod_{k=1}^{n} i_k$, where i_k is the size of the k^{th} dimension of the hypercube E. We can then assign to each cell, $m_{i,j} \in M$, the probability, ρ_{ij}, of transitioning from $e_{i_1,i_2,\dots,i_n}$ to $e_{j_1,j_2,\dots,j_n}$ with consideration given to the exponential divergence or convergence of the system at the transition. The probability value, ρ_{ij}, assigned to cell, $m_{i,j} \in M$ is simply the number of times in E the transition from $e_{i_1,i_2,\dots,i_n}$ to $e_{j_1,j_2,\dots,j_n}$ is encountered, normalized by the total number of single step transitions in E with respect to the local divergence or convergence of the system at the transition point. We refer to this matrix as the Ergodic Transition Matrix (ETM) of E.

The proposed methodology uses ETMs as the data base for classification. Given a set of time series data, acquired for various class labels, models are built through the transformation of that data into ETMs. One ETM is created for each time series. The model ETMs are then grouped by class label forming the training set of the classification algorithm. The test set of the algorithm is formed in similar fashion. Once the training and test sets are formed the classification algorithm uses the Nearest Neighbor methodology for determining the class label of each ETM in the test set.

The Nearest Neighbor methodology is a standard machine learning technique as discussed by Witten and Frank (2005). The Nearest Neighbor methodology assigns a data set the class label of the class whose members most closely match the data set being classified. In the case of the proposed chaotic classification methodology, the class label is assigned based upon the Euclidean distance between the members of the training set and the ETM of the time series being classified. Given a set of ETMs grouped by class label $c \in C$ the proposed algorithm assigns to a time series I the class label of the group of ETMs which meets the criteria in Eq. (1).

$$class_I = min_{c \in C}\left(\sum_{i,j=0}^{N} \sqrt{\left(m_{ij}^{I} - m_{ij}^{c}\right)^2}\right) \tag{1}$$

An additional benefit of the proposed classification methodology is that it may be used in a real time format through the use of moving windows of data. Given a real time signal which is assumed to be deterministically chaotic, and a model of ETMs built as described above, a buffer of data, representing a finite number of orbits of the system in phase space, is collected. Once the buffer has sufficient content, an ETM can be created for the buffered data and compared to the ETM models as described above. The class label of that comparison can be logged and the first data point, or even first orbit, of the buffer can be removed and new data added. This form of classification continues as the buffer is replenished, thereby offering real-time classification of the time series.

CASE STUDY

The case study presented in this paper involved five subjects performing four levels of a task each day for three days. The tasks performed consisted of four different levels of the Multi-Attribute Task Battery (MATB), a well-proven workload generator in the field of operator performance for 20 years with broad applicability (Amegard & Comstod, 1994). These levels are described below during the performance of each MATB task of a known workload level, the ECG of the participant was recorded for use by the classification algorithms.

Four levels of MATB formed the tasks performed in this case study. These levels represented four different levels of difficulty. Two levels, MATB A and MATB C, were kept similar to illustrate the accuracy of the methodology. However, the level of difficulty was randomized to reduce adaptation due to learning and so that the subjects would not inadvertently anticipate the difficulty of future levels based upon the current level. Each subject experienced the same sequence of levels each day they performed the tasks, although these levels were randomized between subjects. Table 1 describes the four levels of MATB used in the case study.

The subject's perceived workload for each task was recorded using the Bedford rating scale. The Bedford workload scale allows the subject to assign a numeric value between 1 (low) and 10 (high) to the level of workload they perceived during a task (Roscoe & Ellis, 1990) using a rubric based decision tree. The Bedford rating tool was developed to support evaluation of aircrew workload during task performance. However, it has been shown to be effective in non-aviation tasks as well (Sukthankar, 1997). The Bedford ratings were used for the class labels in the presented case study.

Table 1. MATB parameters used in the case study.

Task Name	System Monitoring Settings (Seconds between Failures)	Resource Monitoring Settings (Seconds between Failures)	Tracking Settings (Joystick Response/Jitter)
MATB A	10	10	Low/Low
MATB B	4	6	High/High
MATB C	15	15	Low/Low
MATB D	20	20	Low/High

In the presented case study, subjects were asked to record their perceived Bedford ratings. A subjective workload assessment panel in the Cognitive Assessment Tool Set (CATS) (Schnell, Hamel, et al., 2011; Schnell, Postnikov, et al., 2011; Schnell, Melzer, & Robbins, 2009) was used to record the subject's subjective ratings as a ground truth for later use in building a classification model. This software recorded the perceived ratings for each task and stored them in a log file for later use.

Apparatus

The apparatus used in the presented case study consisted of a Portable Computer with monitor, keyboard, mouse, joystick, and a device for capturing the ECG signal. During performance of the MATB tasks, the subjects were restricted to the use of the keyboard and joystick only. Figure 3 depicts the apparatus used.

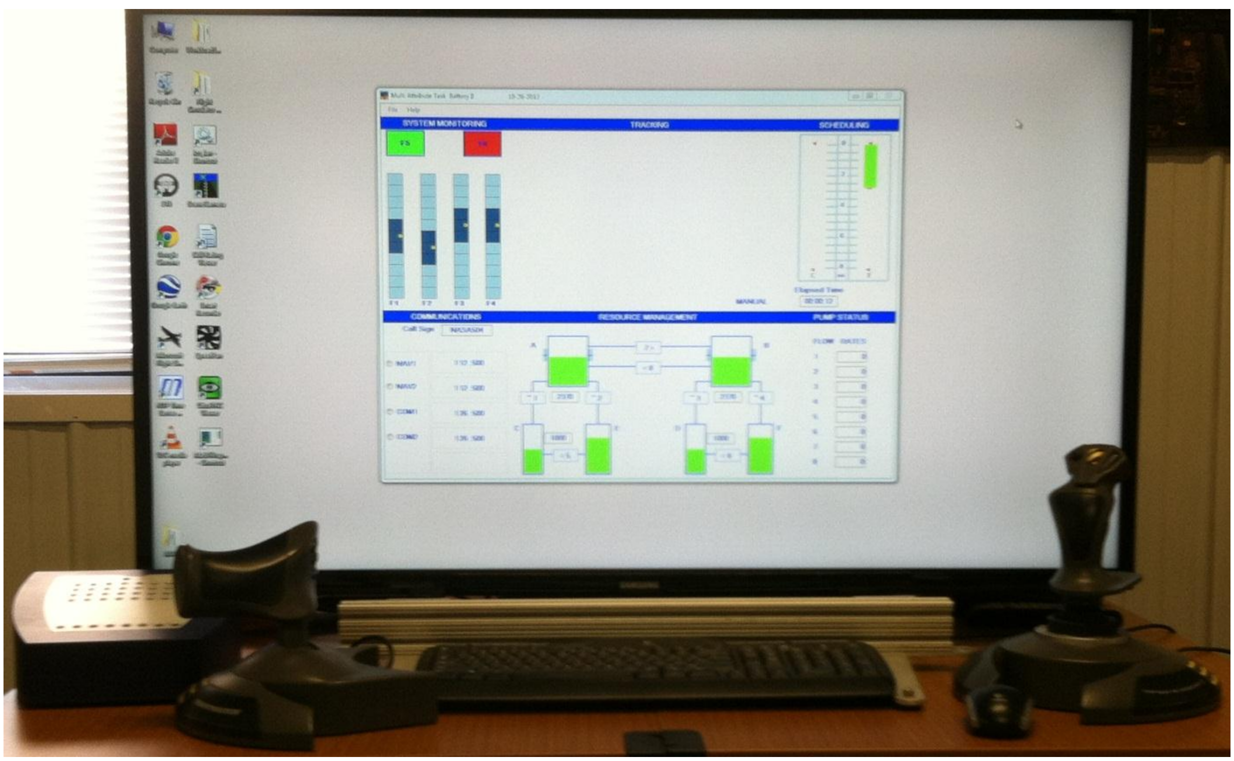

Figure 3. Apparatus used for the presented case study.

The ECG signal was captured from the subjects via a three lead ECG monitor. The monitor was attached to the subject via electrode patches placed in the standard three lead configuration. This sensor then attached to a QuickAmp© amplifier which relayed the amplified signal to the pc and was recorded using the Cognitive Assessment Toolkit System (CATS) (Schnell et al., 2009) developed at the Operator Performance Laboratory of the University of Iowa. This system records physiological, and environmental, signals to a MySQL database for later analysis. The data used in this case study was stored in such a manner. Since the ECG signal forms the input to the proposed classification methodology, proper collection and storage of that data was critical to the experiment.

Case Study Results

The case study consisted of five subjects performing a series of four MATB tasks for each of the three consecutive days for which the study was conducted. The subjects recorded their Bedford ratings using the software described above. ECG signals were captured from each subject while performing each task.

The ECG signals and the self-reported subjective workload scores from Day 1 were used to form the models for the classification methodology. These signals were grouped by task, thereby creating five ETMs (one for each subject) for each task level. These ETMs were assigned a class label of task name. The ECG signals from Days 2 and 3 were then classified using the proposed methodology. Analysis was performed to determine the accuracy of the classification methodology based upon a binary correct/incorrect scoring.

The daily self-reported subjective workload ratings were averaged for each task. However, to illustrate the specific ratings recorded, Table 2 shows the subjects' perceived workload recorded as Bedford ratings for Day 1. Figure 4 depicts the average Bedford ratings reported for the three days of the study. In Figure 4 the tasks are ordered by difficulty rather than name. As can be seen, in general the subject's perceived MATB C and MATB A tasks as fairly low difficulty, MATB D as moderate difficulty, and MATB B as a fairly difficult task.

Table 2. Bedford Ratings for the MATB tasks performed on Day 1.

Subject	MATB A	MATB B	MATB C	MATB D
Subject 1	2	4	2	4
Subject 2	5	7	4	6
Subject 3	5	8	5	6
Subject 4	3	6	2	5
Subject 5	4	8	5	6

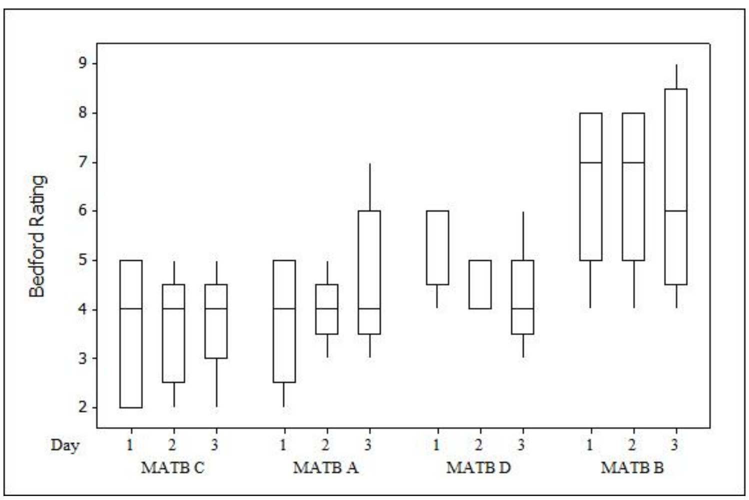

Figure 4. Reported Bedford ratings for the three days of the study. For each day of the study, the five subjects performed four differing levels of MATB. Therefore, each bar represents the reported workload of the five subjects for that task on the given day.

The classification of Day 2 and 3 tasks were performed using Day 1 tasks as the models as described above. The proposed classification methodology performed very well using the ECG signal as the sole input. Figure 5 plots the results of classifying the workload of the subjects via their ECG for Day 2 using the Day 1 models. Each task is labeled with the associated average Bedford rating label from the Day 1 data. Thus, MATB A had a label of 3.8, MATB B was labeled 6.6, MATB C was labeled 3.6, and MATB D was labeled 5.4. This classification resulted in 95% accuracy, using the binary correct/incorrect measurement for the classes. However, that metric underestimates the performance of the classifier which achieved a Pearson Correlation of 0.999. It should be noted that the one misclassification of the Day 2 data determined that a MATB C task had a MATB A workload rating. The average reported workload of those tasks was MATB C = 3.8 and MATB A = 3.6, therefore, even that misclassification is relatively minor.

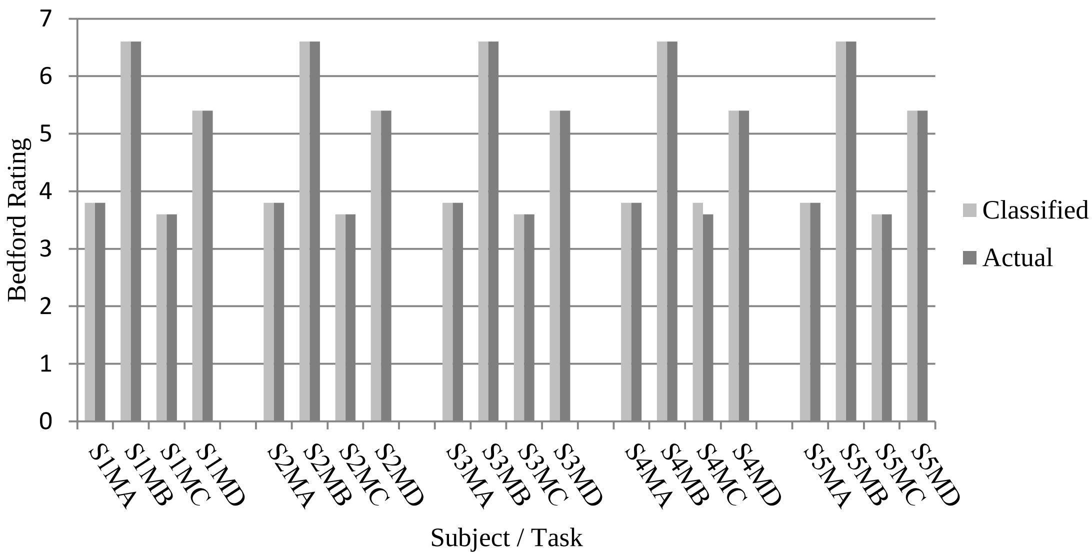

Figure 5. Results of classification of day 2 tasks using day 1 models

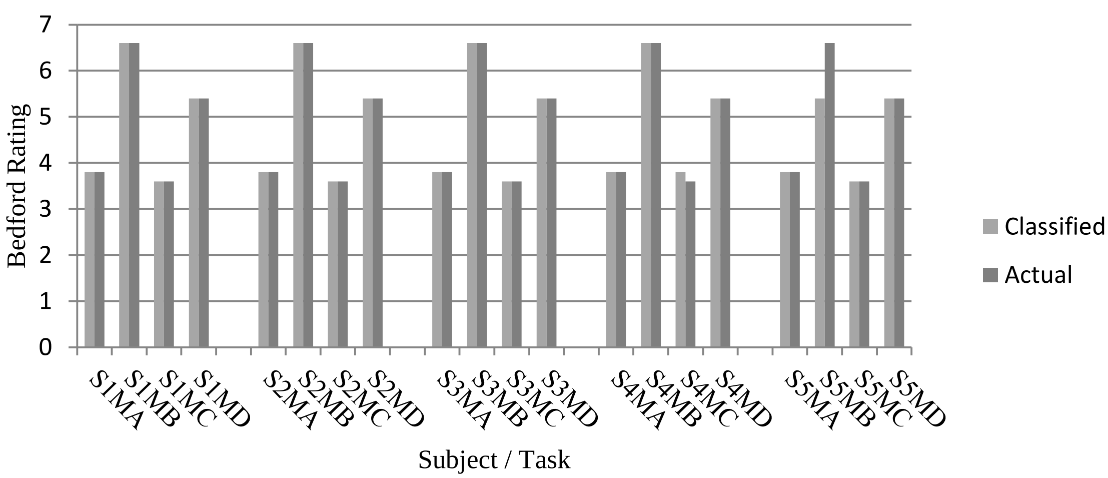

Figure 6. Results of classification of day 3 tasks using day 1 models

Figure 6 plots the results of classifying the subject's workload while performing the tasks on day 3 using the models from day 1. This classification resulted in 90% accuracy, using the binary correct/incorrect measurement for the classes. However, that metric underestimates the performance of the classifier which achieved a Pearson Correlation of 0.97. It should be noted that the two misclassifications of the Day 3 data determined that a MATB C task had a workload rating of an MATB A task and that a MATB B task had a workload rating of an MATB D task. The average reported workload of the tasks in the first misclassification were MATB C = 3.8 and MATB A = 3.6, therefore, that misclassification is relatively minor. The second misclassification determined a MATB D task to have a workload rating of an MATB B task. This is also a minor misclassification given that MATB D's average workload rating for day 1 was 5.4 while MATB B's average workload rating was 6.6, which is, again, a relatively minor misclassification in terms of rating scale magnitude.

In addition to the after action review classification, the authors used the models created from the data collected on Day 1 to perform real-time classification of workload for Day 2. In the real-time paradigm, the subject's data is collected into a buffer of a given length. The buffer is classified using the ETM methodology and its workload is reported. This use of the Chaotic Physiology Classification technique produces a real-time workload metric that may, or may not, change throughout the performance of the task. Two examples of the results of real-time analysis are given in Figure 7 below where the left panel illustrates the results of Subject 2 performing the MATB D task, and the right panel represents the results of Subject 4 performing the MATB A task. In Figure 7 the heavy dark line represents the classified workload while the lighter solid background represents the average reported workload.

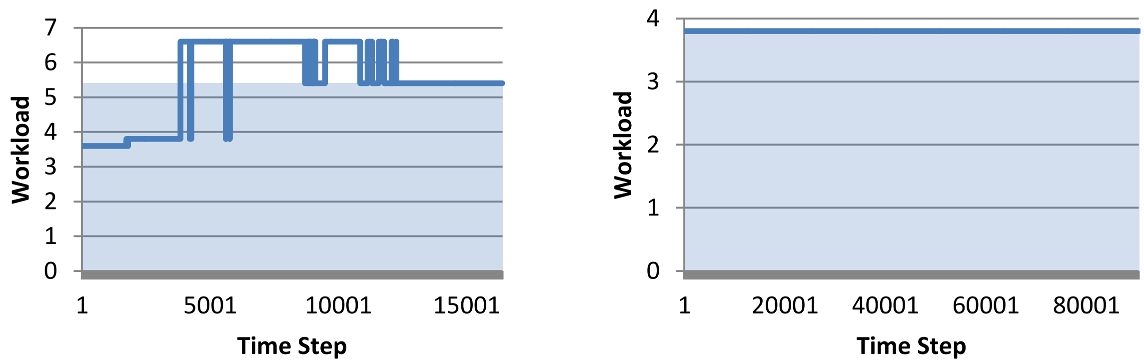

Figure 7. Examples of Real-Time Workload Classification

As can be seen from Figure 7, the proposed methodology is capable of accurately classifying workload in real-time. In fact, the real-time classification of all subjects for days 2 and 3 produced Pearson coefficients identical to those from the discrete after action reviews. The thoughtful reader may inquire whether or not the ETMs are simply detecting a statistical presence within the normal time series signal. The authors were also concerned about this and therefore performed an ANOVA on the time series data. This analysis showed that a statistical correlation between the original time series signal and the workload did not exist. Equipped with that knowledge, the accuracy of the proposed classification methodology becomes even more remarkable.

CONCLUSIONS

This paper presents a novel methodology for classifying human workload using ECG signals. The proposed methodology considers the signals to be from a deterministically nonlinear, chaotic, source. Therefore, transformation of the time series signals into an embedding phase space was presented to better access the dynamics of the system. Presentation was given to partitioning, or course graining, the phase space for the purpose of developing a matrix of transitions. The matrix of transitions is used by the classification algorithm in conjunction with a nearest neighbor methodology for determining the class label of new data.

Also presented in this paper was a case study in which five subjects performed four MATB tasks daily for three days. The purpose of the case study was to validate the classification methodology. Results illustrated the high degree of accuracy with which the proposed methodology classified human workload using the ECG signal. Further, the study illustrated that group models, those made up of data from a group of subjects involved in the study, accurately classify the data without necessity of individual modeling for each subject. The methodology presented in this paper will be utilized in training and research environments to assist in determining participant workload levels in real-time and after action.

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