A Wrist-Worn Biosensor System for Assessment of Neurological Status

D. Cogan-*IEEE Student Member*, M. Baran Pouyan-*IEEE Student Member*,
M. Nourani-*IEEE Senior Member*, J. Harvey, D.O.

Abstract - EEG based monitoring for the purpose of assessing a patient's neurological status is conspicuous and uncomfortable at best. We are analyzing a set of physiological signals that may be monitored comfortably by a wrist worn device. We have found that these signals and machine based classification allows us to accurately discriminate among four stress states of individuals. Further, we have found a clear change in these signals during the 70 minutes preceding a single convulsive epileptic seizure. Our classification accuracy on all data has been greater than 90% to date.

I. Introduction

A. Background

The proliferation of wearable sensors allows effective and inexpensive monitoring of situations and ailments that could previously be monitored only at great expense and at the discomfort of the subject. Assessment of a person's neurological state, however, still requires the use of either surface or implanted electrodes. Such EEG based monitoring is conspicuous and uncomfortable at best. We are studying the feasibility of gathering information about the neurological state of an individual based on resultant physiological changes that can be effectively and comfortably monitored on an ongoing basis.

We looked for physiological metrics that can be monitored by a device resembling a wristwatch. Unlike a device using electrodes attached to the head, such a device would be unobtrusive, comfortable and easy to wear. Heart rate, skin temperature and wrist movement can all be easily monitored here. In addition, electrodermal activity, which is a function of changes in sympathetic neural activity and is also known as skin conductance, can be measured at the wrist [1]. Arterial oxygenation can be measured by a wrist worn device using a finger cuff.

One possible application of our platform is seizure detection and/or prediction. In the late 1950s, John VanBuren studied seizures and the physiological changes that accompany them [2], [3]. In 1970, S. Viglione's group made the first serious effort at seizure prediction. Other research groups followed, but none were successful [4]. In 2002, the First International Workshop on Seizure Prediction was held in Bonn, Germany [5]. Other workshops were held at approximately two year intervals, the most recent, IWSP6, in November of 2013. The goal of these workshops was a collaborative effort to make seizure prediction a reality. Seizure prediction contests were held in the third and fourth workshops, and workshop participants held high hopes for success [6], [7].

Participants in IWSP6 [8] were excited about progress made by Neurovista. This group took a slightly different tact. Instead of trying to predict specific seizures in time to warn the patient, they provided feedback which indicated a high, medium or low probability of a seizure in the near future. Average alert time prior to a seizure was 114 minutes. Neurovista's efforts used EEG analysis and brain implants [9]. If sufficient neurological changes occur to allow time periods of high seizure probability to be determined by reading EEG, perhaps parallel changes in physiological metrics also occur. If so, a wearable device can be developed to provide warning to patients without requiring them to undergo brain surgery.

B. Motivation and Contribution

The next question, then, is whether our platform is monitoring signals that might actually change prior to a seizure. Our study of the literature indicates that we are. A number of researchers [10], [11] and [12] have observed extreme heart rate (HR) changes at the beginning of some types of seizures. At least two researchers [13] and [14] have found indications that arterial oxygen level (SpO2) changes may occur before seizure onset. In conjunction with physical motion (accelerometry data - ACCEL), changes in electrodermal activity (EDA) have been found to effectively indicate the onset of convulsive seizures [15]. Finally, the authors of a survey paper published last year commented that no one has yet investigated temperature (TEMP) as a possible signal for detecting seizures [16]. Consequently, we believe our platform is monitoring a set of metrics that have an excellent possibility of providing insight into the neurological changes of a person wearing it, at least if the changes precede a seizure.

II. Stress Assessment Methodology

A. Physiological Changes Caused by Normal Stresses

Fig. 1 provides a flow chart for the processing of data from our "Healthy Subject" experiment. We collected data using two off-the-shelf components: an Affectiva Q Curve [17], which monitors EDA, TEMP, and ACCEL; and a Nonin 3150 Wireless WristOx2 Oximeter [18], which monitors HR and SpO2.

To be ready for practical use in case a wrist band or finger cuff came loose, data from our two devices was

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D. Cogan, M. Baran Pouyan, and M. Nourani are with the Quality of Life Technology Laboratory at The University of Texas at Dallas, Richardson, TX 75080.{diana.cogan, mxb11223, nourani}@utdallas.edu. Phone: 972-883-4391.

Dr. J. Harvey is with the Texas Epilepsy Group, Neurological Clinic of Texas, Dallas, TX 75251. jhharvey@texasepilepsy.org.

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checked for validity. If the Affectiva Q electrodes lose contact with the skin, the EDA reading will drop out. We considered using a low pass filter on the EDA data to eliminate possible dropouts, but finally decided that we would remove more legitimate variations in the data than dropouts. TEMP and ACCEL data were not affected by temporary loss of contact between electrodes and skin. Consequently, all data recorded by the Affectiva Q was treated as valid.

The Nonin WristOx2, on the other hand, flags invalid data from the finger cuff. Dropouts during the experiment on normal stress were infrequent and brief (less than 5 samples at a time). As neither the HR nor the SpO2 level were changing rapidly during these tests, we used the last good data point to replace dropouts.

The data from each of 20 subjects was separated into four classes: *relaxation, physical stress, cognitive stress and emotional stress*. Because we were dealing with a small amount of data (less than an hour) from each of our test subjects, the data in each class was divided into (short) six second windows. Like other approaches that deal with data streams, we considered a sliding window with 50% overlap to overcome sensitivity of exact size and position of windows [19]. The data in each window was analyzed for four basic statistical features requiring a minimum of computational power: *mean, maximum, minimum, and the change from beginning to end of the window*. In addition, a frequency analysis was done on the accelerometer data by counting the number of movements per window. As our ultimate goal is to create a real-time, wearable system, computation must be kept to a minimum to minimize the processor power requirements.

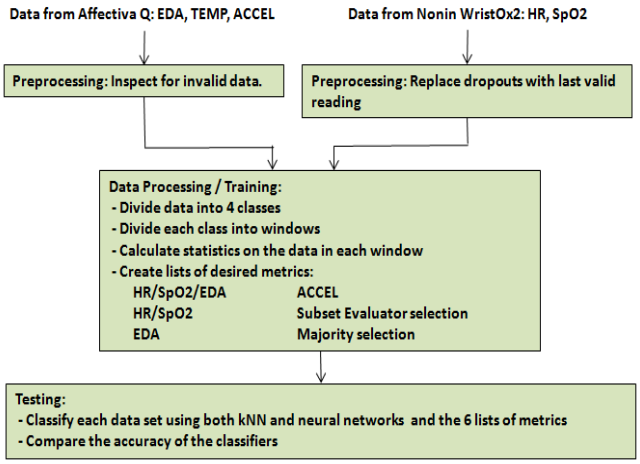

Fig. 1: Normal Stress Data Flow

To verify that all of our sensors were useful for distinguishing our four classes of activities, WEKA was used to perform a *best first correlation based feature selection (CFS)* of the most useful features from each of our 20 data sets. As the feature selection varied from one data set to the next, we continue to consider all the sensors of our current platform to be necessary [20].

To classify each data set, we used two well-known machine learning techniques: 1) k-nearest neighbor (kNN) with 3 neighbors, and 2) neural networks. KNN is an analytically tractable and effective method for classifying noisy training data. It classifies each new instance X by finding the training instances $<X_i, Y_i>$ with the minimum distance to newcomer instance X according to the Euclidian distance:

$$||X-X_i||=[(\sum_k(X_k-X_{ik})^2]^{1/2}, \quad (1)$$

where k in (1) is the index of the k^{th} feature of any data instance.

Neural networks are robust, fault tolerant systems that are suitable for classifying noisy and incomplete patterns. Further, they handle medical diagnosis problems well [21]. We used a 3-layer feed forward neural network with one input for each metric fed into the classifier and one output for each of our four classes. A network with one hidden layer of 4 neurons provided optimal performance. The learning rate and momentum are 0.3 and 0.2, respectively. Fig. 2 shows the structure of our neural network [22].

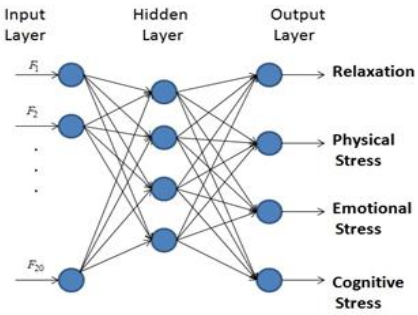

Fig. 2: Neural Network

As we expected, our algorithms were able to classify data windows into the four different activity classes most accurately when given the most information. However, the neural network algorithm ran as much as several minutes faster when given less data to process.

B. Physiological Changes Caused by Seizure

Rather than attempting to deal with the HR and SpO2 dropouts in the entire data file, we decided to handle them window by window. Because we are now dealing with several hours of data at a time, we used longer, 30 second windows to analyze the data, but kept the 50% overlap. After the data was divided into windows, each window was scanned for HR and SpO2 dropouts. Valid data was extracted and statistical analysis performed on it. If there was no valid data in the window, a flag was returned.

The following statistical features were extracted from each window of the data: *maximum, minimum, mean, mode and standard deviation*. The resulting metrics were used to classify the data into *preseizure* and *nonseizure* classes using the same k-nearest neighbor algorithm used on the normal stress data. Again, we were looking for features that require minimal processing power in anticipation of designing a real-

time wearable device. Fig. 3 shows the procedure we used to analyze this data.

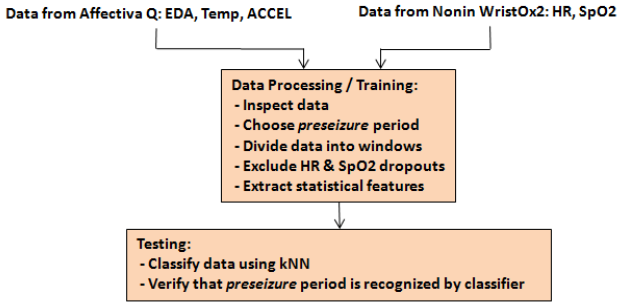

Fig. 3: Procedure for Analyzing Seizure Data

III. Experimental Results

A. Classification for Normal Stresses

In our previous work [23], we sought to determine whether our chosen metrics provided sufficient information to distinguish common types of stresses. Our success in this endeavor lends support to our belief that we can gain insight into a person's neurological state through his physiological signals.

Our "Healthy Response to Stress" test asked volunteers to alternately relax and perform three predesigned tasks. During the four relaxation sessions the subject was asked to sit quietly and listen to soothing music. The objective of these sessions was to establish a baseline for the physiological metrics we were measuring. That way we could see how each metric changed during the three tasks and what the sensitivity and specificity of each metric was.

The data from one volunteer is shown in Fig. 4. Table 1 shows the confusion matrices for this data set. Both of our algorithms were able to classify the data from all 20 subjects with greater than 90% accuracy. Fig. 5 summarizes these results. The Subset Eval selection category in Fig. 5 was the CFS choice of metrics for each subject. The 7 features most commonly selected by CFS for the individual data sets (*z-mean, z-max, z-min, y-mean, x-mean, temp-mean and eda-mean*) were used to analyze all 20 data sets as well. Fig. 5 shows those results as the Majority selection.

B. Classification for Seizures

Collection of seizure data is being done under an IRB protocol at an Epilepsy Monitoring Unit (EMU) in Dallas, TX. Electroencephalography (EEG) seizure annotation has been done by our medical consultant using NeuroWork software [24]. Our devices are time synced to the EEG equipment so that we are certain of seizure onset and offset times.

We have six hours of data from one epileptic patient who suffered a dyscognitive seizure with secondarily generalized tonic-clonic seizure (also known as a complex partial with secondarily generalized tonic-clonic seizure) while wearing our devices. The graph is shown in Fig. 6. The vertical lines show the three time periods of interest to us:

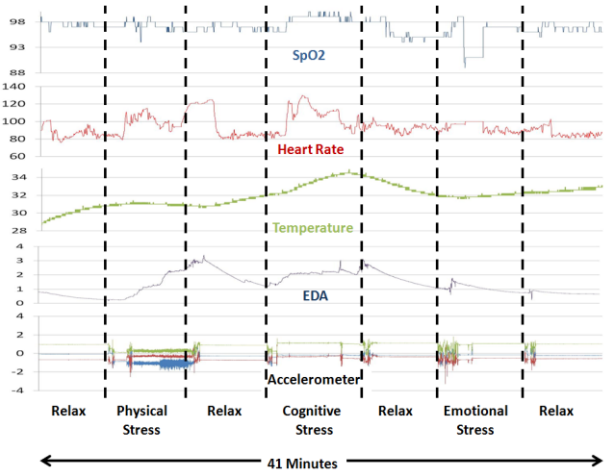

Fig. 4: Data from One Healthy Subject

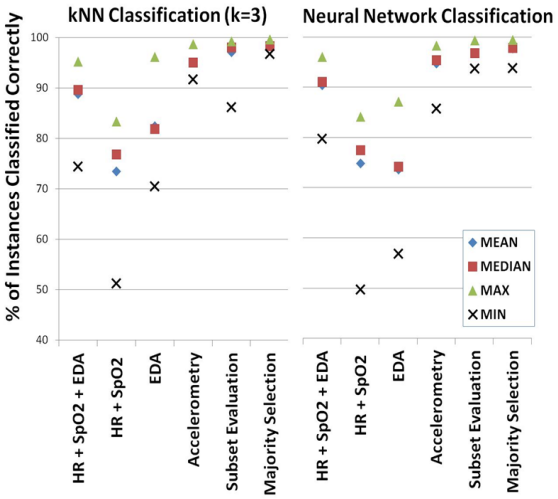

Fig. 5: 20 Subject Classification Using (a) kNN, (b) Neural Network

- Period 1: precedes the seizure by more than 70 minutes
- Period 2: 70 minutes immediately preceding the seizure
- Period 3: includes and follows the seizure

Visual observation of the graph in Fig. 6 shows definite changes during the 70 minutes prior to the seizure onset. Use of our kNN algorithm confirmed that Period 2 is distinctly different from Periods 1 and 3, as shown by the confusion matrix in Table 2. Significantly, no *preseizure* windows have been categorized incorrectly. (Note: Periods 1 and 3 are both classified as "Other" in Table 2.)

IV. Conclusions

We were excited by the discovery that our classification algorithms were able to distinguish, with great accuracy, the type of stress a person was under based on statistical data from our five sensors. To the best of our knowledge, we are the first researchers since John M. Van Buren (late 1950s) to look at this many extra-cerebral metrics. Further, we are in a better position to analyze the data we are collecting because

TABLE 1: Confusion Matrix for Fig. 4 -Data (Percent)

Class	kNN Classifier				Neural Network Classifier			
	Relaxation	Physical Stress	Emotional Stress	Cognitive Stress	Relaxation	Physical Stress	Emotional Stress	Cognitive Stress
Relaxation	98.0	0	5.9	0.9	98.7	0	0.8	0.9
Physical Stress	0	99.1	0	0	0	99.1	0.8	0
Emotional Stress	1.0	0.9	94.1	0.9	1.0	0.9	98.4	0
Cognitive Stress	1.0	0	0	98.2	0.3	0	0	99.1
Sensitivity	98.0	99.1	94.1	98.2	98.7	99.1	98.4	99.1
Specificity	97.1	96.8	98.4	97.1	98.9	98.7	99.0	98.7
Precision	97.7	100	95.5	96.6	99.5	99.1	96.2	99.1
Accuracy	97.5				98.8			

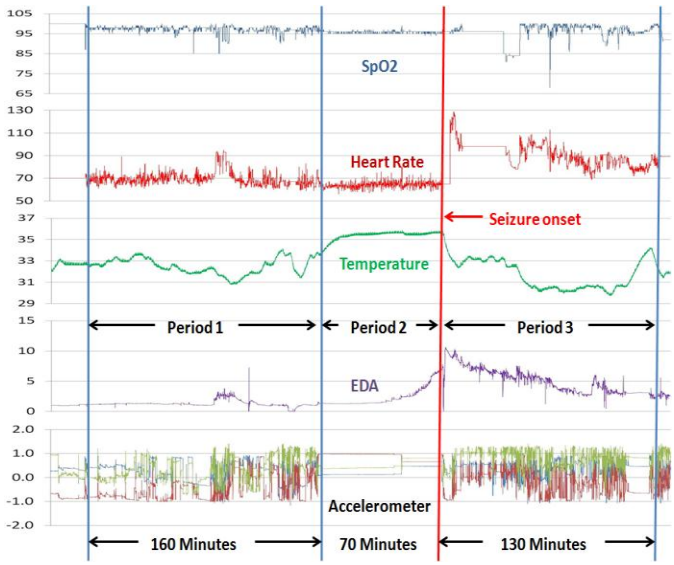

Fig. 6: Data from One EMU Patient

TABLE 2: Confusion Matrix for Fig. 6 Data (Percent)

Class	Other	*Preseizure*
Other	100	2.1
Preseizure	0	97.9
Sensitivity	100	97.9
Specificity	97.9	100
Precision	99.4	100
Accuracy	99.5	

Van Buren lacked the technology to 1) monitor patients with minimal disruption to their comfort and 2) perform the signal processing and data mining that we are able to do. The extreme heart rate change at the beginning of the seizure is similar to that observed by other researchers. The large increase in EDA response at the beginning of his seizure is also expected for a convulsive seizure. Loss of HR and SpO2 data during the clonic phase of a seizure was expected, and underscores the importance of replacing our current device with a reflectance oximeter as soon as possible. The almost complete lack of motion during Period 2 gives it a *calm before the storm* feel. Our discovery of a *preictal* footprint prior to this seizure leads us to believe that we have selected a set of sensors that will enable us to recognize *preictal* footprints prior to other epileptic seizures as well. If a patient's *preictal* footprint appears in similar form before each seizure, we have a realistic possibility of predicting seizures where others have failed. We need data from many more patients and seizures before we can draw definite conclusions.

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