A Low-Power Multi-Physiological Monitoring Processor for Stress Detection

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***Abstract*—Personal monitoring systems can offer effective solutions for human health and performance. These systems require sampling and significant processing on multiple streams of physiological signals. The processing typically consists of feature extraction, data fusion, and classification stages that require a large number of digital signal processing and machine learning kernels. In order to be functional, however, the processing architecture needs to be low-power and have a low-area footprint. In this paper we present such a design for a personalized stress monitoring system with a flexible, multi-modal design. Various physiological and behavioral features were explored to maximize detection accuracy with both SVM and KNN machine learning classifiers. Among 17 different features from 5 sensors, heart rate and accelerometer features were found to have the highest classification accuracy to detect stress in the given dataset. While KNN classifier accuracy outperforms by 2%, it requires significantly larger memory and computation compared to the SVM classifier. Therefore, we chose the SVM classifier for hardware implementation. The post-layout implementation results in 130 nm CMOS technology show that the SVM processor occupies 0.2 mm^2 and dissipates 20.2 mW at 125 MHz. The proposed processor takes 800 ns to classify each input and consumes 16.2 nJ. The overall classification accuracy of this system is 96%.**

***Index Terms*—Multi-modal Monitoring, Machine Learning Classifiers, Stress Monitoring, Wearable, ASIC**

I. Introduction

Personalized health monitoring systems have become popular with the recent explosion in wearable technologies. These systems enable the acquisition of various physiological and behavioral data that can be used to make general inferences about the state of the human. Generally, these systems consist of three related processes: (1) a sensor front-end to capture and digitize physiological signals; (2) real-time digital signal processing to preprocess signals, to select and extract features, and to ultimately make intelligent use of the data; and (3) a radio transmitter to transmit relevant information to user or medical personnel (Figure 1) [1],[2]. In this paper, we propose a low-power multi-modal physiological monitoring processor with specific interest in classifying periods of stress. Previous research has demonstrated success in determining drivers' stress by monitoring multiple physiological signals, such as electrocardiogram (ECG), electrodermal activity (EDA), electromyography (EMG) and respiration, while driving a vehicle in a prescheduled route [3].

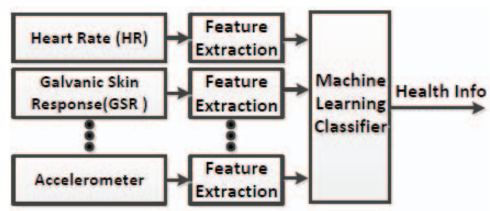

Fig. 1: Block diagram of a multi-physiological health monitoring system containing data acquisition by sensors, feature extraction, and machine learning classifier to generate result.

Instead of a more constrained environment such as a vehicle, in this experiment we utilize data from a naturalistic shooting task in which stress was manipulated by incorporating different feedback modalities for making incorrect decisions. Our explicit goal is to determine an algorithmic model from which the level of stress could be determined using multi-modal, physiological and behavioral signals. First, we examine what combination of features are able to best differentiate the level of stress from the available data. Second, we optimize the classification by testing both Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) machine learning algorithms. Finally, we demonstrate a hardware design that implements stress detection based on SVM classifier. Our work demonstrates that stress detection in this task can be accomplished with low-power and low-area ASIC design which is able to combine features of body movement and heart rate to achieve good classification results.

II. Multi-parameter Feature Extraction and Classifier

A. Description of Dataset

The data used to evaluate the performance of our system consists of multi-physiological and behavioral recordings from 15 subjects [4]. The participants performed a shooting task in a simulator in which they had to discriminate enemy versus friendly targets and decide to shoot or refrain respectively. Three levels of stress were induced by manipulating performance feedback on incorrect trials in a blocked design: low (none), medium (visually displayed), and high (electric shock). Importantly, each subject experienced all blocks, however they were randomly assigned for each subject. For this paper, only the low and high stress conditions were studied. Shock was delivered using a ThreatFire^{TM} belt with a 200 ms, 50 μA pulse for incorrect decisions. Figure 2 illustrates the simulation environment from which data has been acquired.

B. Feature Extraction

During the experiment, participants wore a physiological monitor, Equivital EQ02^{TM}, which captured 3 axis accelerometry data, ECG, chest expansion, peripheral capillary oxygen

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Fig. 2: 300 degree simulator to collect the multi-physiological data during different levels of stress [4].

Feature No.	Sensors	Features
1 to 5	HR	Mean HR, Std HR, LF-HRV HF-HRV, LF/HF ratio
6 to 11	Accel	Mean of X,Y and Z axis Standard deviation of X,Y and Z axis
12 to 15	EDA	EDA freq., EDA ampli., EDA duration, EDA area
16	Resp. Rate	Mean RR
17	SpO_2	Mean SpO_2

TABLE I: 17 features extracted from five physiological sensors per each window of 35 seconds

saturation (SpO_2), and EDA. Total of 17 features used in the experiment were derived in 35 second windows and are elaborated in Table I. Each of these windows were assumed to represent a period of low or high stress depending on the feedback modality provided during that time period. To ensure consistency in the stress condition, the 10 beginning windows and the last window of each period were ignored. Several features were derived from ECG. Heart rate (HR) was determined as the duration between peaks of the QRS complex, from which both a mean and standard deviation were determined (mean HR and std HR respectively). Low frequency heart-rate variability (LF-HRV) was determined by a Fourier transform of the R-R time series in the 0-0.08Hz frequency band which represents sympathetic nervous system activity. High frequency heart rate variability (HF-HRV) is the same analysis but in a different frequency band, 0.15-0.5Hz which is modulated by the parasympathetic system activity. The LF to HF ratio (LF/HF) is used as an index of autonomic balance (increase in stress level will increase this ratio) [3],[5]. Six accelerometer features (mean and standard deviation) were derived from each of the 3 axis accelerometer data. We extracted four features from the EDA: number of startle responses in the window (EDA freq.), the sum of the response magnitude (EDA ampli.), the sum of response duration (EDA duration), and the sum of the estimated areas under the responses (EDA area) [3]. Finally, the mean of respiration rate (mean RR) and the mean of SpO_2 in each window were also derived as features.

C. Machine learning Classification

We utilized binary class SVM and KNN machine learning classifiers to detect the stress level in various time periods. In order to find the best combination of the features, we examined the classification accuracy of each feature for all individuals independently. We used a custom MATLAB script to train the classifiers and determine the accuracy of the classification. The KNN algorithm classifies test data by knowing the labels of the K nearest neighbors using a distance metric (Euclidean distance in this study). The SVM classifier works by finding the maximum margin hyperplane. Test samples are then classified using the function shown in (1), where $\overrightarrow{VS}_i$ is a support vector, $\vec{X}$ is a test vector and b is bias.

$$f(x) = sign(\sum_{i=1}^{NUM\_SV} (\overrightarrow{VS}_i.\vec{X}) + b) \qquad (1)$$

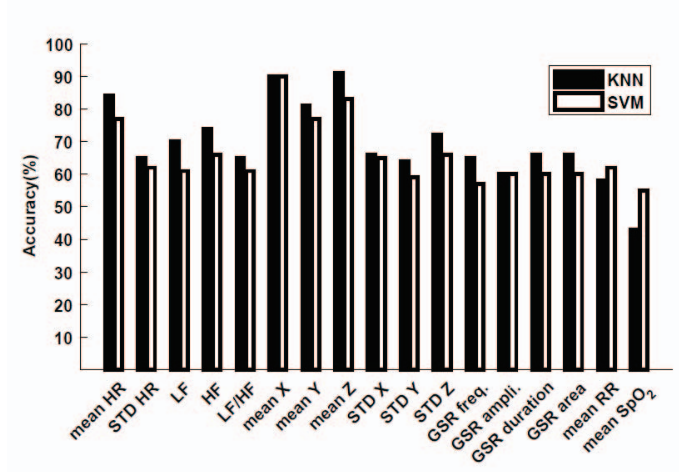


Fig. 3: The stress detection accuracy using multi-physiological sensors and corresponding features for average of 15 individuals. The features with highest accuracy are highlighted.

TABLE II: Hardware complexity analysis of KNN and SVM, n: size of training data, m: size of test data, p: No. of features, and s: No. of support vectors.

Algorithm	Multiplications	Additions	Memory Requirement
KNN	$p \times n \times m$	$(p-1) \times n \times m$	$n \times p$
Linear SVM	$p \times m \times s$	$m \times (p-1) \times s$	$p \times s$

Figure 3 shows the average accuracy for all 15 individuals for each feature when using the SVM and KNN classifiers. The mean heart rate and mean accelerometer data in all 3 axes achieve the highest accuracy across individuals. The KNN classifier outperforms the SVM classifier in terms of accuracy by roughly 2%. However, since KNN requires to compute distance from all training data for each classification, the memory and computation requirements are significantly higher than the SVM [6],[7]. With the SVM, the training step can be performed offline to find the number of support vectors, which is much less than the size of training data in the KNN method. Table II compares the memory and arithmetic operation requirements by KNN and SVM. Given the increased computational and memory requirements which leads to larger footprint, increased power requirements and the relatively small difference accuracy, in this work we use SVM for hardware implementation. Figure 4 shows the accuracy level of SVM classifier for HR and accelerometer features separately and combined feature set.

III. SVM hardware Implementation

Figure 5 shows a detailed architecture of linear SVM processor used for stress monitoring system based on four

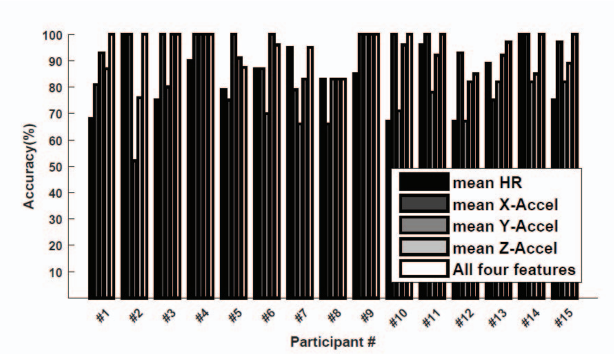


Fig. 4: The comparison of accuracy level for multi-modal feature set with separate features from heart rate and accelerometer

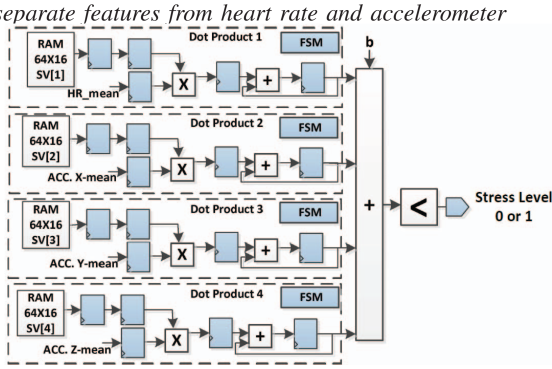
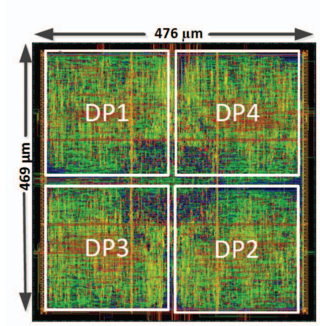


Fig. 5: Block diagram of the hardware implementation of SVM classifier. Block RAMs on the left (1 Kbit each) store 64 support vectors.

extracted features from heart rate and accelerometer sensors. The proposed parallel pipelined architecture is flexible for variable number of features. The support vectors (SV), bias (b) and other coefficients were calculated using the SVMtrain MATLAB function. Each RAM memory block is loaded with precomputed weighted support vectors from a trained model for each feature. There are sufficient registers in this design to store the intermediate results in the pipeline scheme. The classifier receives the features derived in 35 second windows as testing input. The dot product operation runs between the testing data and all supporting vectors available in RAM memory blocks. This is followed by the parallel dot product operation, which is added with bias parameter to find the predication result.

IV. ASIC Implementation Results

Several previous research studies have examined hardware implementation of SVM on ASIC [6],[7],[8]. However, this work to the best of our knowledge presents the first ASIC design for a multi-modal monitoring application using SVM. The hardware processor was synthesized, placed and routed in the 130 nm TSMC CMOS technology. Figure 6 shows the post-layout view and results for the proposed SVM processor for a stress monitoring system. We used a standard-cell register-transfer level (RTL) to Graphic Data System (GDSII) flow using Cadence tools. The hardware was implemented using Verilog to describe the SVM architecture, synthesized with Cadence RC compiler, and placed and routed using the Cadence SoC Encounter. The SVM processor runs at 125 MHz and consumes 20.2 mW. The prediction for each window



SVM Processor Implementation Results

Technology	130 nm, 1 V
Logic Utilization	91.4%
Area	0.2 mm^2
Frequency	125 MHz
Total Power	20.2 mW
Latency	800 ns
Energy	16.2 nJ

Fig. 6: Layout view and post-layout implementation results of the proposed multi-modal SVM processor. The highlighted regions indicate the location of four dot product components on the chip.

of data (35sec) takes 800 ns resulting in 16.2 nJ energy consumption per window.

V. Conclusion

In this work, we demonstrated accurate detection of stress by utilizing multiple physiological signals and hardware design capable of delivering this classification. Out of 17 features considered, our analysis indicated that using heart rate and accelerometer signals for determining the level of stress generated the most accurate classification results with both KNN and SVM classifiers. The average accuracy for all individuals was approximately 96%. Finally, we demonstrated the ASIC implementation of SVM classifier which minimizes power consumption and maintain a low-area footprint, which are critical when considering a real-world application. Our results have direct relevance for the development of a near real-time stress monitoring system.

VI. Acknowledgment

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