Movement identification in Affective Health – a mobile biofeedback monitoring system

Iuliana Silvăşan, Per Kreuger, Pedro Sanches, Elsa Vaara, Marie Sjölinder

***Abstract* — Affective Health is a mobile biofeedback monitoring system that measures galvanic skin response, pulse and movement, data which is sent through Bluetooth to the mobile phone where it is displayed on an interactive interface. The representation of the movement in the first versions of the system did not include any information about the type of activity the user performed. For an improved version of the system we have therefore tried to infer movement more precisely. A Naïve Bayes classifier was used for movement identification. The classifier was cross validated and tested on data obtained from 6 persons. We present quantitative results for different scenarios and selection of features and conclude that the proposed techniques indeed worked very well.**

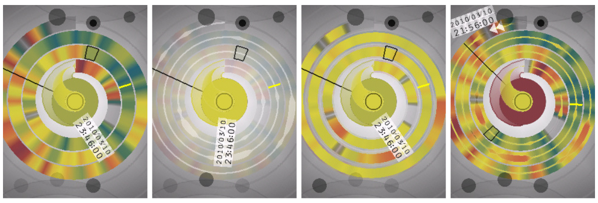
***Keywords* — movement identification, Naïve Bayes, biofeedback monitoring, user empowerment.**

I. The Affective Health System

Affective Health is a system that makes use of wireless technologies and mobile phones to allow users to gain information about their bodily experiences in everyday life. This information has the purpose to support the person in noticing stressful situations and become aware of behavioral patterns [1].

Previous research has shown that heart rate and galvanic skin response are bodily parameters that manifest themselves differently based on the context the user finds herself in [2]. The galvanic skin response (GSR) is an indicator of arousal and heart rate (HR) provides further information about the physical and emotional state of the user. Heart rate correlated with movement will provide information that will indicate the presence of factors that are not related just to physical activity. While involved in a physical activity, high perspiration and heart rate will be normal. If the movement stops, but HR and/or GSR remain elevated, it may suggest the presence of a stressful factor that can be psychological or physical. We chose to leave some of the interpretation of the biodata to the users as in unconstrained settings it is difficult to automatically and accurately infer meaning from the biofeedback [2].

In the initial versions of Affective Health, movement was detected using a tri-axial accelerometer placed in the user's pocket without indentifying the type of activity. We found that although the users could already relate to an unclassified index of movement, it was difficult for some users to know what activity the movement illustration refers to (see Fig. 1(b)) and place it in time in relation to all the information visualized. This gave us the motivation to attempt to classify types of physical activities for future versions. Providing information about the type of movement, the user is supported in better differentiating between activities, seeing patterns in her life and more easily reflect on bodily reactions and behaviors. Such information helps the user map herself in time, it gives her focal points in the interface to relate to. For example, it can be of value to visualize that one has climbed up the stairs every morning the past three days when arriving at work. To extract and provide this information, movement identification was done using two accelerometers, not just for more accuracy, but also to provide possibilities to further asses more information, e.g. energy expenditure from the sensor placed on the waist.



(a) (b) (c) (d)

Fig. 1. The Affective Health interface. (a) Arousal (color); (b) Movement (shape of the inner channel); (c) Heart rate (color); (d) All 3 measurements (heart rate's color inside movement's shape). A complete cycle in the spiral corresponds to one minute, hour, day respectively; these specific views are chosen by pressing the buttons in the upper part of the screen. The buttons for the biofeedback are in the lower part of the screen.

Previous body of research [3] proved that identification with the digital artifact through what it expresses about the user is a primary factor influencing how much the users will like the artifact in the long term. Other important aspects about a mobile sensing/monitoring system refer to the ability of the system to encourage and trigger personal growth, to stimulate changes and support achievement of behavioral goals [3], not just the technology that it incorporates.

We found three experiential qualities that are important to consider when designing systems with biosensors for everyday use, where context is either not available or hard to infer: *openness* to interpretation from the user, *aliveness* through interactive history from the gathered data [4]. These qualities served to improve engagement with the system and helped users interpret the data coming from the sensors. The chosen interface (Fig. 1) is focused on the

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understanding and vocabulary of a regular user for whom the association of emotions with colors (blue, green for relaxation and yellow, orange, red for different levels of emotional/physical intensity) is done on an everyday basis and it is part of modern culture and art. Using numbers or graphs do not always resonate with the meaning found by the user in her experience of stressful, emotionally difficult situations. Having personal biofeedback mirrored back at her, the user "paints" the interface herself and in turn, this supports self-identification with the representation, impels to self-reflection and motivation for prolonged usage.

II. Related Work on Movement Identification

Using accelerometers for acquiring information about the user's movement can be non-intrusive and still provide meaningful data both for the user to reflect upon and also for an expert if needed, i.e. doctor, trainer. Compared with a pedometer, it provides richer information and could better distinguish steps as the pedometer fails to do this when the user is moving very fast and it does not provide any information regarding the intensity of the activity [5].

With respect to health related applications, the movement identification focus has been on using this information for monitoring elderly or partially impaired individuals. Recognizing abnormal motions, e.g. falling, determines a certain response of the system, e.g. calling an ambulance, the care giver or other medical personnel [6]-[8]. The goal in these cases is to identify and report for expert evaluation, not for user self-empowerment.

Providing information about movement from accelerometers is meaningful for *fitness/wellness applications* mainly by calculating energy expenditure [9] and amount of movement. FitBit [10] is a system that logs calories burned, steps taken, distance traveled, sleep quality and sends them to a website. Certain information (e.g. food) is manually added and visualizing results is done using graphs.

UbiFit Garden [11] application uses Bluetooth as a communication medium between the sensors and phone. The interface illustrates a garden which is populated with flowers depending on the physical activity and additionally with butterflies when a chosen fitness goal is achieved. Still, the system does not give the user information about the type of activity performed.

There are various methods that can be used for movement identification, including base-level classifiers, meta-level classifiers, Hidden Markov Models (HMMs), neural networks, fuzzy logic and others. Comparative studies show that Naïve Bayes and Decision Trees perform best in identifying movement from accelerometer signal, while Plurality Voting would be a good choice out of the meta-classifiers [12],[13]. Reference [8] have used HMMs, reference [14] used neural networks. Reference [9] used a Naïve Bayes classifier and the list could continue, as most classifiers have been approached for this category of applications.

HMMs are useful in modeling human behavior by recognizing a sequence of activities, but our interest is to motivate the users to observe such sequences themselves, see connections between individual activities and reflect upon the pattern they create. Neural networks perform well, but require great computational power for the training and have a black-box behavior, hiding the logic of the process. Meta-classifiers need base-level classifiers to work upon, therefore we have chosen to concentrate on one of the most promising base-level classifier – Naïve Bayes – for our movement identification. It is computationally efficient when dealing with even great number of attributes and robust also in situations that contradict the assumption of statistical independence of the individual attributes. The learning and inference process is straight-forward, allowing a better understanding of the results and ease in adapting it.

III. Movement Identification for the Affective Health System

A. The recognition system

The recognition system consists of a sensing module, a feature processing module and a classification module that aims to differentiate between standing, walking, climbing up and down the stairs and running. In the Affective Health system the sensing module is separated from the other modules which are integrated in the phone application. Certain applications that make use of movement identification and rely on sensors built-in to the mobile phone are not very efficient because the accelerometers lack a reference system. The interpretation of the data obtained in this manner is affected by the mobile phone's position, location, orientation and few researchers take it into consideration [12].

The sensing module is based on two tri-axial accelerometers connected to an acquisition hub. They have a fixed position on the body, thus having a reference system. Two scenarios have been tested and compared. The first scenario consisted of placing one sensor on the back at the waist level and the other one on the ankle, and the second scenario meant placing one sensor on the back (waist level) and the other one on the leg, above the knee, to the side.

The feature processing module extracts certain characteristics from the raw signal using windows with 50% overlap as they are proved to be successful for feature extraction [13]. The chosen features – mean, standard deviation, power spectrum over three intervals of frequencies (1-5 Hz, 5-10 Hz, 10-50 Hz) are calculated for each axis of the accelerometer and the correlation is calculated between the axes of the two sensors and between the axes of each sensor, resulting in 45 features. Their usefulness is also verified by previous research [12],[13],[15]. As human motion is generally characterized by low frequencies, it was not necessary to explore the power spectrum further. For each of the sensor placement scenarios, the features were computed using a window of 2 seconds with 1 second (sec.) overlap and a window of 4 sec. with 2 sec. overlap, for comparison.

The classification module consists of the implementation of the Naïve Bayes logic in the application. Having trained the classifier, when given a new set of features, it will try to predict the movement class that could have generated the features by choosing the class with the highest computed probability.

B. *Method*

For the algorithm to provide meaningful results and be widely applicable, the data was collected from 7 users under controlled experiments for both scenarios. This means that the subjects were supposed to enact a certain sequence of motions including walking, running, climbing up and down the stairs and standing in between each of these activities. The 'standing' parts had the purpose of differentiating between activities and make the signal easier to process (visualizing it, separating training sets). At this moment it was not necessary to identify other stationary positions, as they do not have a visible representation in the interface (standing and sitting will have the same illustration) and don't have the potential of a focal point in the representation. Movement enactment has a greater potential in generating recall [16] and by obvious illustration, trigger self-reflection.

The classifier was trained on the data corresponding to one person and tested on the same dataset using a 10-fold cross-validation, taking into consideration a Gaussian distribution of the signal. The training was done using different sets of features obtained by leaving out certain features from each of them, for comparison. The cross-validation for each set was performed 100 times and the final result was obtained as an average of all these values. The data from the six other users were used to verify the classifier for its robustness against individual variations in movement patterns.

All these steps were performed both for the raw signal and the filtered signal. To filter the signal, a sixth order Butterworth low-pass filter was applied.

C. *Signal processing*

All sensors are connected to an acquisition hub that is using the Bluetooth medium to forward the data to the mobile phone. The Sony Ericsson P1i mobile phone receives the data at 1000 samples/second. For movement identification the sampling frequency was not reduced, but the entire signal was used in order to not lose information about the type of motion.

At first, the raw signal was evaluated. Fig. 2 shows evident differences between the activities for the accelerometer on the leg (column on the left) and ankle (column on the right) for a time period of 10 seconds. The accelerometer on the back is not presented as its position is the same in both wearability scenarios.

Fig. 3 presents the raw signal for several activities corresponding to 37 minutes and 42 seconds of samples for the accelerometer on the leg, 38 minutes and 18 seconds of sensor readings for the accelerometer on the ankle and the corresponding filtered signal.

IV. RESULTS OF THE CLASSIFICATION

The performance of the classifier being trained with all 45 features over windows with 50% overlap is presented in Table 1. A small window could capture sudden changes in movement, but the results show the classifier cannot always accurately identify it given the 2 sec. window (Table 1). Filtering the signal provides an improvement in the classification especially for the 2 sec. window, suggesting it would be a good decision to choose the proper filter for the signal in such a situation. In the case of a window of 4000 samples (4 sec.), the improvement is in the order of the first decimal, being not so problematic.

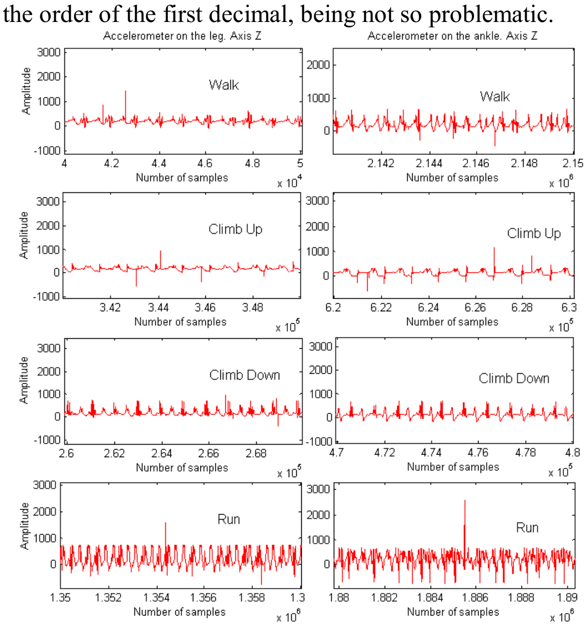

Fig. 2. Raw signal. Axis Z of the accelerometer. 10 sec.

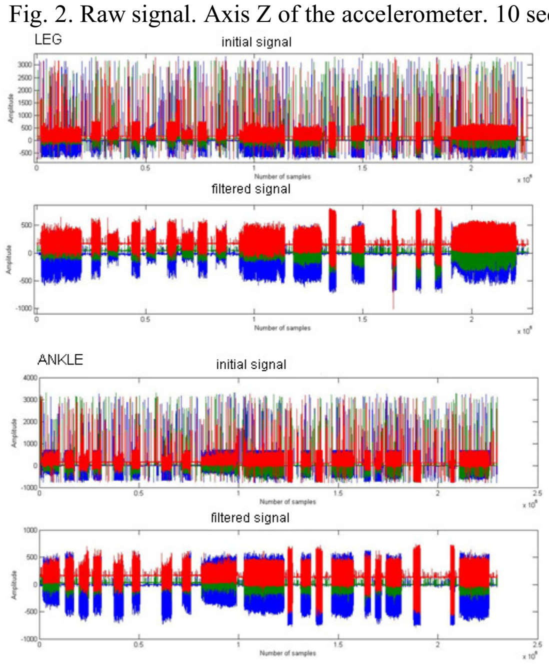

Fig.3.Raw and filtered signal. Leg and ankle accelerometer

Having the sensor on the ankle, there is more noise due to the impact of the leg with the ground, explaining the inferior performance in Table 1, compared with scenario one (sensors on the back and above the knee), where the impact is deadened as the sensor is higher up on the leg.

Table 2 presents an average decrease in performance compared to the results in Table 1 for a selection of subsets of the full feature set. "Remove correlations" refers to removing all correlation features, but as one attribute at a time. "Remove power spectrum" means removing all power features (there is one for each frequency interval per axis), but for one axis at a time. “S1”, “S2” refer to the sensor placement scenarios. The “insignificant” decrease refers to differences in the order of the 4th or 5th decimal.

TABLE 1: CLASSIFIER PERFORMANCE WITH ALL THE FEATURES

Scenario One			
Raw signal/Window size		Filtered Signal/Window size	
2 seconds	4 seconds	2 seconds	4 seconds
99.73%	100%	99.86%	100%
Scenario Two			
96.87%	97.55%	97.44%	97.71%

TABLE 2: AVERAGE DECREASE OF PERFORMANCE

	Raw signal/Window size		Filtered Signal/Window size	
	2 seconds	4 seconds	2 seconds	4 seconds
	Remove correlations			
S1	0.01%	insignificant	0.08%	insignificant
S2	1.78%	0.15%	1.17%	0.35%
	Remove power spectrum			
S1	0.01%	insignificant	insignificant	insignificant
S2	0.22%	0.03%	0.02%	0.07%

Removing the mean and standard deviation one at a time affects the output in the order of the 2nd decimal for both scenarios, for each test result.

Removing one feature at a time does not have a great impact on the classifier and the average of these differences is not high. Therefore we decided to use all the features to define the final classifier. It was decided to filter the signal and calculate the features over a 2 sec. window.

The classifier was tested given these circumstances on the data from the other 6 users. The averaged results are presented in Table 3. Their datasets were divided into activities and each activity was tested individually. The classifier performs extremely well in identifying standing, walking and running regardless of the known context of the user. When the climbed stairs had a significantly smaller height (c.s) than the ones that determined the signal used for training (c.h.), the activity was classified as walking (Table 3, c.s. with an average for the movements of both scenarios) regardless of the scenario. Although the raw data is meaningful enough for the classifier, it affects the maximum and minimum values that could be detected and used for step identification and further analysis of the data.

TABLE 3: PERFORMANCE ON THE DATASETS FROM 6 USERS [%]

Climb down		Climb up	Walk	Run	Stand
c.h.S1	99.89	99.80	99.91	99.95	100
c.h.S2	97.85	97.76	98.07	98.23	99.56
c.s.	walk	walk	99.90	99.93	99.64

V. CONCLUSION AND FUTURE WORK

The comparative study that we performed showed that the performance of the classifier was good in all cases, with small variations. We chose as final classifier the one trained with the full set of attributes extracted over a 2 sec. window (with 50% overlap) on the filtered signal because we would like to further explore identification of sudden movements, i.e. tics, a different indicator of intense situations, emotionally (stress) or physically, and help the user be more aware of them and control them if desired. As we do not want to enforce many restrictions on the user regarding sensor placement, we’ll consider the two scenarios in the future as well. This may lead to building pre-defined movement type profiles to choose from. This will be useful if solutions for better differentiating between activities, based on the characteristics of the environment (e.g. stairs), are not found. As we have seen that the chosen Naïve Bayes classifier performs well, we need to move on to discovering design solutions for representing this new information about movement.

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