

Automated Detection of Sensor Detachments for Physiological Sensing in the Wild

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ABSTRACT

Body area sensor networks measure biomedical signals from subjects continuously, as they go about their daily lives. Signals measured in these conditions are affected by anomalies, such as artifacts and noise. Some anomalies can be corrected, if detected in real-time, for example, ECG electrode detachment. We present energy and computationally efficient algorithms for the detection of sensor detachment, developed for the AutoSense system.

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1. INTRODUCTION

Wearable, unobtrusive sensors are revolutionizing the conduct and outcomes of health science studies by enabling capture of physiological data from people in natural environments. Unfortunately, the quality of the signal that can be captured from natural environments does not meet the scientific community's stringent data quality requirements. Sensor noise, motion artifacts, and sensor failure are common occurrences that reduce the quality of the signal. In a laboratory setting, such problems can be corrected with sensor calibration, correct application of the sensor, and careful monitoring of the signals [1]. These tasks are traditionally handled by laboratory staff. However, in natural environments, it is impractical for lab staff to continuously monitor subjects as they go about their normal daily life. To meet the stringent data quality requirements of scientific studies, the data quality controls of laboratory environments are needed in the natural environment.

In this work, we propose automated, continuous monitoring of sensor data that occur in natural environments. When a data quality problem is detected, the system can guide the wearer of the sensors through the process of correcting the problem and restoring the quality of sensory measurements.

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We implement a data quality monitoring and correction module on an Android mobile smartphone using the AutoSense body-area sensor network and the mStress mobile inferencing framework [2]. AutoSense [3] is a body area sensor network comprised of a chest band suited with five sensors: Electrocardiogram, Respiration Inductive Plethysmograph, Body Temperature, Ambient Temperature, and 3 Axis Accelerometer. The mStress framework is a rich context-inferencing framework for the Android platform. It collects physiological data from wireless wearable sensors (such as AutoSense), computes features from the data, and inputs the features to machine learning algorithms to produce inferences about the user. This system is primarily used for collecting physiological, behavioral, and affective markers of stress and addictive behaviour.

The data quality module monitors physiological signals transmitted to the smartphone from the AutoSense wearable sensor suite. It detects detachment or loosening of three types of sensors from a person's body, electrocardiogram/galvanic skin response (ECG/GSR), respiratory inductive plethysmograph (RIP), and body temperature (TEMP). We will demonstrate the detection of these events, as well as a series of instructions displayed on the smartphone to help the user correct the problem.

2. SENSOR DETACHMENT ALGORITHMS

Each algorithm is a classifier that outputs a decision, based on features computed from the data. To address design constraints of algorithms for low power devices, such as energy and computational efficiency, and also to simplify the algorithm development, we explore the use of a *divide and conquer* strategy, and build the complex classifiers as a combination of simpler ones. Each such simple classifier constitutes a module, and the final decision is obtained by combining the outputs of the individual modules. This simplifies the algorithm development. Each module can be executed only if needed, improving the overall energy and computational efficiency. This approach is inspired by techniques such as boosting in machine learning and hierarchical activation in sensor networks, but we do not prove a formal relationship here. Our goal is to continue this work towards a framework to simplify the development of complex classifiers.

2.0.1 ECG signal

Many algorithms for detection of artifacts and noise in ECG signals can be found in the literature, e.g., [4, 5]. Here, we focus mainly on anomalies that can be corrected, if detected in real-time, such as electrode detachment, loose electrical

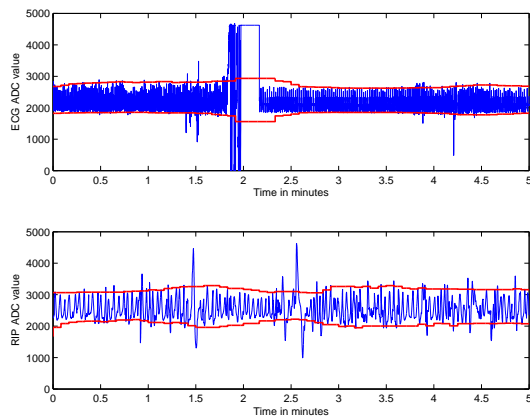


Figure 1: Typical ECG (top) and RIP (bottom) signals, with envelope.

connectors, bad electrode contact, and excessive noise. The output of the algorithm is either *signal okay*, *electrodes detached*, or *signal degraded*. We build the classifier by combining the output of the following simpler decisions: (1) *Signal is saturated at a low or high level*, (2) *signal has a large number of discontinuities*, (3) *signal has low amplitude*, (4) *signal has a large number of spikes*. Signal saturation indicates electrode detachment, large discontinuities indicate loose contacts, while large spikes indicate excessive noise. Noise can be produced by physical movement or problems with the electrodes. Only in the latter case, the signal is flagged as *degraded*. To rule out movement as cause of noise, we use accelerometer measurements. If the signal has low amplitude, but not excessive noise, it is not clear if there is a problem with the electrodes. In that case we check if the morphology of the signals corresponds to an ECG waveform. This operation is computationally expensive and thus, it is performed only when low signal quality is suspected. To measure the signal amplitude, we developed a simple yet robust and efficient envelope detector. Figure 1(top) shows a typical ECG signal and the estimated envelope.

2.0.2 Respiration signal

RIP signal is obtained from a respiration band, worn around the chest. As opposed to ECG signal, there is little work in the literature on detection of anomalies in RIP signals. The algorithm we present is similar to the one developed for ECG. The output of the algorithm is either, *band off*, *signal degraded*, or *signal okay*.

We have observed that RIP signal is less affected by noise than ECG, but it is affected by strong physical movement and misplacement or incorrect adjustment of the respiration band. Similarly to ECG signal, band detachment can be detected by signal saturation, loose contacts by large discontinuities in the signal, and loose band by low signal amplitude. Signal amplitude can be estimated using an envelope detector. Figure 1(bottom) shows a RIP signal and its envelope. If low amplitude is detected, we first check the morphology of the signal to determine if it corresponds to a normal respiration signal, and if not, we inform the user.

2.0.3 Body temperature signal

Body temperature is obtained from a probe attached to the body. If the probe is detached from the body, the signal is zero. When the probe is attached to the body, the signal increases until it reflects the body temperature [6]. Except for small variations, such as those produced by ambient temperature changes or physical movement, if the probe is correctly attached, the measured temperature must be above a given threshold. The output of the algorithm is, *probe detached*, *probe loose*, or *signal okay*. We have observed that, if the probe is inside the clothing, but not correctly attached to the body, the TEMP signal presents oscillations, while, if the probe is away from the body, the signal is zero. In a first stage, the algorithm for the TEMP signal, determines if the signal is either zero (*probe detached*), or above a threshold. If this is not the case, in a second stage, the algorithm determines if the signal is increasing or decreasing. Only if the signal is below a threshold, and not increasing, *probe loose* is flagged.

3. EVALUATION

We evaluated the algorithms on data that was collected as part of a 22 subject user study. For each signal we determined the percentage of the data that would have been flagged as *low quality* by the algorithms. We found that about 7 percent of the ECG data was flagged, while 9 and 18 percent of the RIP and TEMP data were flagged, respectively.

4. DEMONSTRATION PLAN

In this demonstration the presenter will wear the complete AutoSense system suit and show the measured signals on the screen of the smartphone, as well as the output of the data quality algorithms. The presenter will generate different artifacts and noise in the signal, by moving or detaching the sensors. The viewers will be able to observe the effect of such anomalies in the signals, and the response of the data quality algorithms on the smartphone, in real time.

5. REFERENCES

- [1] M.S.M. Yarvis. Challenges in Data Quality Assurance in Pervasive Health Monitoring Systems. In *Future of Trust in Computing: Proceedings of the First International Conference Future of Trust in Computing 2008*, page 129. Vieweg+ Teubner Verlag, 2009.
- [2] Andrew Raij, Patrick Blitz, Amin Ahsan Ali, and et. al. mStress: Supporting Continuous Collection of Objective and Subjective Measures of Psychosocial Stress on Mobile Devices. Technical report, University of Memphis, 2010.
- [3] AutoSense Project. <http://sites.google.com/site/autosenseproject>, 2009. [Online; accessed 26-August-2010].
- [4] RM Farrell and BJ Young. Effect of lead quality on computerized ECG interpretation. *Computers in Cardiology*, 31:173, 2004.
- [5] G.G. Berntson, K.S. Quigley, J.F. Jang, and S.T. Boysen. An approach to artifact identification: Application to heart period data. *Psychophysiology*, 27(5):586–598, 2007.
- [6] T. Oka, K. Oka, and T. Hori. Mechanisms and mediators of psychological stress-induced rise in core temperature. *Psychosomatic Medicine*, 63(3):476, 2001.