# Improved Signal Quality Indication For Photoplethysmographic Signals Incorporating Motion Artifact Detection

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***Abstract*— Wearable monitoring systems have gained tremendous popularity in the health-care industry, opening new possibilities in diagnostic routines and medical treatments. Numerous hardware systems have been presented since, which allow for continuous acquisition of various biosignals like the ECG, PPG, EMG or EEG and which are suited for ambulatory settings. Unfortunately, these flexible systems are liable to motion artifacts and especially photoplethysmographic signals are seriously distorted when the patient is not at rest. A lot of work has been done to reduce artifacts and noise, ranging from simple filtering methods to very complex statistical approaches. With regard to the PPG, certain quality indices have been proposed to evaluate the signal conditions. As movements are the primary source of signal disturbances, the relation between the output of a signal quality estimator and acceleration data captured directly on the PPG sensor is focused in this work. It will be shown that typical motions can be detected on-line, thereby providing additional information which will significantly improve signal quality assessments.**

## I. INTRODUCTION

Pulseoximeters have become an indispensable part of routine medical applications and various devices have been developed in the past that are either based on reflective or transmissive measurement principles in order to capture the photoplethysmographic waveform [1] [2]. Clinicians primarily apply pulseoximeters to non-invasively observe the oxygen saturation especially during anesthesia or post-operative treatments. Further, the photoplethysmogram (PPG) has been used to extract other vital parameters like pulse-rate and heart-rate variability [3], respirational activity [4], pulse transit times and blood-pressure indications [5]. It was also shown that a careful morphological analysis of the pulse wave can reveal vascular diseases [6] or provide information about arterial elasticity and aging [7].

Due to its easy applicability, PPG sensors are generally suited for long time measurements in home monitoring scenarios. However, PPG signals acquired in such ambulatory settings are often distorted by motion artifacts which seriously hamper the above mentioned analysis procedures [2] [8]. Many contributions that focus on artifact reduction have been presented since, including methods based on adaptive noise cancellators [9] [10] [11], filter banks [12], Fourier analysis [13], Kalman filters [14], wavelets [15] [16], smoothed Wigner-Ville distribution [17], singular value decomposition [18] or independent component analysis [19] [20].

Next to artifact reduction, automatic quality assessments also play an important role when it comes to succeeding signal analysis and tasks like feature extraction. Based on expert-labeled reference data Sukor et. al have developed a three stage classification process to automatically detect poor pulse quality in the PPG [21]. Li and Clifford suggest to apply dynamic time warping to calculate features out of the PPG which are then evaluated by a neural network to classify the quality of the PPG [22]. Yet some other approaches resort to statistical evaluation of the PPG data to detect motion artifacts [23] [24].

As the majority of signal distortions in the PPG are caused by different kinds of motions of the subject's extremities, raw acceleration data might enhance the capabilities of signal quality estimation. In [25], typical movements which provoke PPG artifacts have been summarized, resulting from an interesting field study that was conducted in a clinical environment. Since different kinds of motions lead to different kinds of artifacts, this work focuses on the automatic classification of different finger, wrist and general hand motions by evaluating features extracted from a three channel acceleration sensor that is directly attached on the PPG fingerprobe. A robust classification of distinct motions will serve as a valuable indicator with regard to the expected signal quality and might help to choose a proper reconstruction approach. For this purpose, a novel five wavelength PPG acquisition hardware equipped with an acceleration sensor directly attached on the fingerprobe has been developed, which is part of a wireless body sensor network.

Next, the quality estimation algorithms proposed by [21] and [22] are applied on the data acquired by our system. In that context, some difficulties regarding these approaches are discussed which support the notion to incorporate acceleration data in PPG preprocessing tasks.

The paper is organized as follows. In part A of the following section the PPG acquisition system is presented whereas part B concerns itself with the experiments conducted in this study. An insight of the most important preprocessing steps with respect to the PPG and ACC raw data is provided in part C. The result section III presents the classification performance of typical motions and depicts the outcomes of the implemented PPG quality estimation procedures. Section IV summarizes the conclusions and gives a short outlook.

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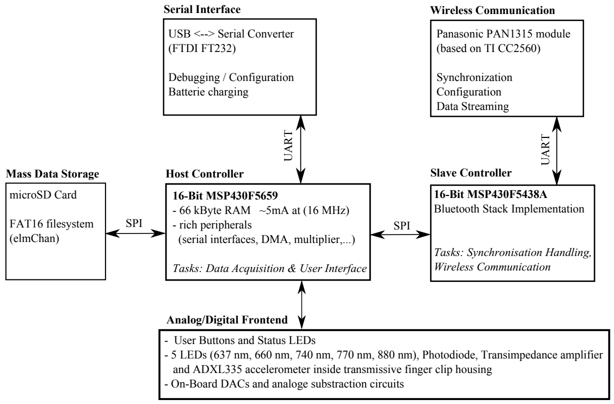


Fig. 1. Block diagram depicting PPG sensor hardware

## II. METHODS

### A. Hardware System

In order to simultaneously record PPG and acceleration data, a new transmissive fingerclip sensor has been developed. The main performance criteria have been set to robust data recordings on a mass storage device, high sampling rates up to 1 kHz, synchronicity among multiple devices, easy applicability and long battery life that allow long-time measurements of at least 24 hours. To meet the above stated requirements, a dual controller architecture has been assembled, which is depicted in Figure 1. An MSP430F5659 serves as the main controller (Master) which controls the analog PPG front-end and runs a FAT filesystem [26] to store the captured raw data on a micro SD-card. The controller is equipped with a generous amount of 66 kBytes internal SRAM, which are used for large buffersizes preventing data lost on sporadic occurring latencies of the SD-card.

To cope with the important and time crucial tasks of wireless timer-synchronization, data transfers and inter sensor network communication, an MSP430F5438A was chosen as the second controller (Slave) which operates a Texas Instruments Bluetooth CC2560 module. As this controller does not have to serve any further tasks, a minimum interrupt latency for incoming packages can be guaranteed, which is essential for the accuracy of the implemented time synchronization.

Both controllers run at 16 MHz and are supplied by a rechargeable 2100mAh lithium-ion battery which is typically used in modern smart phones.

The PPG finger clip houses a photodiode opposite to five surface mounted LEDs with wavelengths of 637nm, 660nm, 740nm, 770nm and 880nm. As mentioned in the previous section, a three channel accelerometer is placed on the PCB inside the finger clip housing. In the current settings, all signals are sampled at 500 Hz using the internal 12-Bit analog/digital converter of the master controller.

### B. Experiments

The main objective of this work aims at identifying typical hand movements by evaluating the corresponding acceleration signals. Therefore, two PPG sensors based on the architecture described in the previous subsection are used in the following experiments. The first finger probe is attached to the index finger of the right hand which will perform the experiments whereas the second finger probe is attached to the index finger of the left hand, which will be kept at rest to provide an artifact free reference PPG signal. Moreover, a three lead ECG (Einthoven I, II and III) is recorded simultaneously.

In order to retain a certain reproducibility, the experiment protocol is partly based on classes of motions conducted in other published works [21] [16] [23] [25] and consists of the following motions: *Bump*, *Disturb finger probe*, *Rest*, *Shake wrist*, *Tap finger*, *Horizontal twitch left*, *Horizontal twitch right*, *Horizontal twitch forward*, *Horizontal twitch backward*, *Vertical twitch up*, *Vertical twitch down*, *Horizontal periodic right/left*, *Horizontal periodic forward/backward*, *Horizontal circle*, *Vertical periodic up/down*, *wrist rotate*, *trembling*.

Ten healthy subjects (age from 19 to 44, 7 male, 3 female) have volunteered to participate in the depicted measurements. Each of the above listed hand-motion-experiments has been conducted for 40 seconds followed by 20 seconds remaining at rest. Out of each 40 seconds experiment period, 25 blocks of 2000 samples have been extracted (blocks overlap 1500 samples). Thus, 250 samples of each experiment are available.

### C. Preprocessing

With regard to the motion detection, only the three acceleration channels in x-, y- and z-direction are taken into account. The succeeding feature extraction is performed on the raw signals, so that no preprocessing takes place. In total, 52 features in the time domain, frequency domain as well as statistical properties are calculated out of each sampleblock. The derived features are then enclosed in a large dataset which also contains the labeled classes presented in the previous subsection. Thus, supervised machine learning methods can be applied to classify the different types of motions.

In this work, a naive Bayes network as well as a multi layer perceptron (MLP) have been implemented to classify the blocks of ACC data according the current hand motions. Both approaches are well suited for later on-line prediction, as the computational complexity is relatively low.

As the signal quality directly depends on occurring motions, the signal quality estimation approaches proposed by Sukor, Li and Clifford [21] [22] are implemented in order to associate detected movements with possible changes of the signals morphology and to explore the performance of both methods on our data. Sukor argues that good PPG pulses have similar amplitude, width and morphology to adjacent pulses and therefore derives a two stage classification process on that basis. In this work, the preprocessing of the PPG signal has been arranged in exactly the same manner, so that the PPG can be classified into three categories: *Good*, *Poor* or *Bad*. The first two classes are mapped to *SukorGood* whereas the third class will be mapped to *SukorBad*.

Li and Clifford basically derive features of a single PPG beat by comparing the pulse to an average beat, incorporating dynamic time warping. These features are evaluated by a neural network classifier which assigns the PPG quality class to either *Excellent*, *Acceptable* or *Unacceptable*. We will map the first to classes to *LiCliffordGood* and the last to *LiCliffordBad*.

## III. Results

### A. Motion Classification

The classification of the acceleration data with respect to different hand motions yielded very promising results. Applying a stratified 10 fold cross-validation, the naive Bayes approach classified 93,1 % instances correctly. The multi layer perceptron was trained using the backpropagation of error method [27]. In a 10 fold cross-validation 95,6% of the classes have been predicted correctly. With the help of a subset size forward selection method, the number of significant features have been reduced to 22 elements. Thus, it seems principally possible to detect and to distinguish between certain hand movements. A closer examination of the signal quality during the different hand motion states might provide a valuable information for following signal processing methods and is discussed in the next subsection.

### B. PPG Quality

As described in the previous chapter, the PPG signal has been automatically classified as either *Good* or *Bad* using the two presented signal quality detection approaches. Figure 2 gives a visual impression of the outcomes of the classification processes. Not surprisingly, there are some discrepancies concerning the output of the two classifiers. It should be mentioned at this point, that Sukor's algorithm is based on heuristically determined thresholds that have to be adjusted to the individual dataset. If the absolute amplitude of a detected pulse for example, exceeds the empirically predetermined threshold, the pulse is immediately classified as bad quality. Therefore, such an approach depends on several environmental factors like the subject's finger thickness, position of the finger probe or even tolerances of the built-in LEDs and photodetector. For that reason, some kind of online adjustments of the given threshold should be considered to avoid unnecessary false-negative classifications.

Detecting the current state of motion might deliver very valuable information that can be used for such recalibration methods. To get a quantitative idea of the PPG-Quality/Motion-State relation, a histogram which is gained by the sum of all datasets is shown in Figure 3. The histogram plots the number of beats belonging to the corresponding quality class. It should be noted, that the two quality estimators implement different peak detectors performing not equally well, which is the reason why the number of

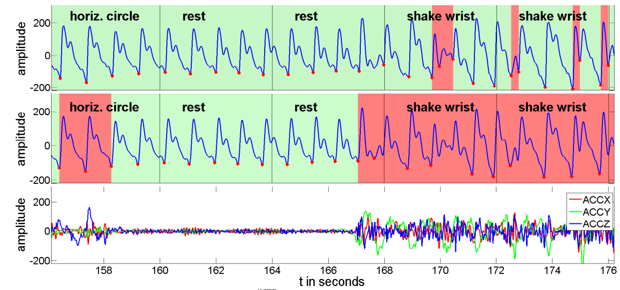


Fig. 2. Classified PPG quality according to LiClifford (top), Sukor (middle) in combination with predicted hand movements. The colored backgrounds represent the estimated signal quality (Red: Bad Green: Good). The blocks of the classified motion are separated by the vertical black lines. The third plot shows the acceleration signals.

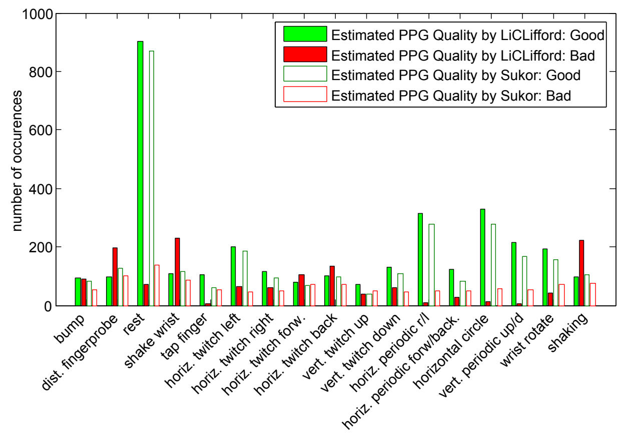


Fig. 3. Estimated quality classes during different exercises

beats extracted by the two approaches is not equal. Between each conducted experiment the subjects remained 20 seconds at rest, which is the reason why there are far more 'rest' states than other experiments. As expected, there are motion exercises where the proportions of bad signals predominate. This information could be used by methods, which require a PPG free of motion artifacts. Moreover, it can be seen that there is a relatively great amount of signal portions that have been classified as bad during the rest state. When inspecting these candidates, one will note that the morphological shape is often intact and the downgrade is due to an improper threshold. One should also keep in mind that the LiClifford Classifier was trained on records drawn from a completely different dataset and therefore might malperform on new unseen data. In that case, the incorporation of the acceleration based detected motion delivers an important indicator for plausibility of the quality classifications.

### C. Hardware Performance

As two controllers have been incorporated into the system design, a robust data acquisition flow can be guaranteed. The master controller spends all its resources without being disturbed on the sampling of the analog front end, generous data buffering and succeeding storage on the micro SD-card. Thus, data lost which typically occur when the system is interrupted at critical time instances can be avoided. Simultaneously, the slave controller can immediately handle incoming wireless Bluetooth packets, which is essential in timer synchronization applications. In the current settings, we are able to record the five channel PPG along with the three channel ACC signals at sampling rates up to 1 kHz without lost of packets. In that configuration the whole module draws approximately 40mA, which allows long-time measurements up to 48 hours.

## IV. Conclusion

In the scope of this work, a wireless hardware system has been developed which is able to record a transmissive PPG accompanied by local acceleration data. The output of two Signal Quality Estimators on our data has been evaluated and some drawbacks were highlighted. Moreover, it was shown, that typical movements which have been reported to severely hamper PPG signal acquisition, can be detected on-line by evaluating the ACC signals. These information have been proven valuable for tasks like signal quality estimation and are very promising for further PPG processing methods, where the state of the current motion might be of great interest. Methods as proposed by [12] for example, might significantly profit from our proposed motion detection, which have to locate artifact free periods in order to start a recalibration sequence of certain reference signals. In the next steps, the proposed method could be used to enhance existing artifact reduction approaches by proper incorporation of the detected motion information. In this paper, only the infrared channel has been considered, leaving out the remaining four wavelength signals, which could contribute further interesting information.

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