ABSTRACT
We propose a new architecture for an handy and motion resistant estimation of the heart rate. We use one infrared light emitting diode at 875 nm and one photodetector encapsulated in a standard earphone device. Two axis accelerometers are used for sensing head movements and provides signals that are further used for activity classification and optical signals enhancement. Accelerometers have also been encapsulated into the earphone so that the complete system is easy to wear, light and highly reliable due to the artefact compensation algorithm. Good performance of the system in a typical sport activities is shown.

KEY WORDS
Heart rate, optical sensors, earphone, artefacts, denoising

1 Introduction
Optical probes have been used for years for measuring biological tissue properties [13]. In particular, blood gas saturation such as $\text{SpO}_2$, temperature, and heart rate. The main advantages of these techniques relies on the noninvasive measurements of vital parameters. One of the most known vital sign is the heart rate. Easy to wear heart rate sensors are based on photoplestysmography (PPG), which has been used widely over the past for the estimation of cardiovascular parameters such as for example pulse oximetry and heart rate [15, 11]. Corruption of the PPG signal arises from influences of ambient light and motion of the subject [11, 12]. These artefacts lead to erroneous interpretation of PPG signals and degrade the accuracy and reliability of PPG-based algorithms for the estimation of cardiovascular parameters. Various methods for improving the PPG technique during motion artifacts and low perfusion of the tissue have been designed [10, 5, 2, 3, 1]. Recently, a fingering sensor has been proposed, which use special mechanical design in order to reduce the effect of motion on the PPG signals [9].

In this paper we propose a new fully integrated heart rate measurement system that is located at the ear (Patent pending). This system is based on infrared (875 nm) optical measurement of the sub-cutaneous blood flow by trans-illumination, together with integrated 2 dimensional accelerometer (2DACC) used to provide a reliable motion reference. Figure 1 shows the system design together with the sensor placement. Mechanically stable and adapted to the ear anatomy, the sensors are less subject to probe-tissue induced artifacts. Moreover, the sensors does not interfere with the functionality of the earphone device.

2 Method
The chosen optical wavelength is 875 nm. The emitter is a light emitting diode (LED), Agilent Technologies HSDL-
4420 and the photodetector (PD) is Osram BPW-34F. The light wave is sent through the ear cartilage and penetrate skin and blood vessels to finally reaching the PD. The PD then transforms the received light intensity \( I(t) \) into a current and then transformed into a voltage \( x_{PD}(t) \).

The PD output signal \( x_{PD}(t) \) together with the two analog output acceleration signals \( a(t) = (a_x(t), a_y(t)) \) have then be conditioned using custom signal conditioning circuits and finally digitized using a PCMCIA National Instruments DAQCard-AI-16XE-50. Sampling frequency was set to 20 Hz, and a digital 2nd order Butterworth band-pass filtering between 0.5 Hz and 8 Hz was used. The Matlab software was used for offline processing of the three digital signals. Subjects were asked to perform alternatively running and walking on a fitness treadmill. The Polar system was used as a reference for comparison.

3 Motion artefact model

The principle of the proposed heart pulse wave sensing resides in emitting an optical infrared (IR) signal at the surface of the body tissue. This signal is then propagated through the tissue where it is submitted to modifications due to reflection, refraction, scattering and absorption. The resulting signal, after propagation through the tissue is grasped by one or multiples optical sensors, which are located at distance of about 2 mm of the optical source. Since variations of optical tissue characteristics are related to variations in the sub-cutaneous blood flow, the received signal can be used for the estimation of the heart rate. For the near infrared wavelength, the light propagation into the tissue is governed by scattering and absorption [13]. The Beer-Lambert equation is generally used to describe the phenomenon of light absorption in biological tissue [13, 11]. Voluntary or involuntary movements corrupt the PPG signal and create motion related artefacts. In presence of motion artefact, the received log-transformed intensity can be rewritten in function of the major contributions as follows [8]

\[
I(t) = I_s(t) + I_{tissue}(t) + I_{motion}(t) + I_n(t)
\]

where \( I_s(t) \) is the source intensity, \( I_{tissue}(t) \) is the static attenuation due to the tissue absorption, \( I_{motion}(t) \) is due to the dynamic changes of the tissue induced by the movement of the ear, \( I_{pulse}(t) \) is due to pulsatile absorption of the blood, and \( I_n(t) \) includes other noise contributions such as measurement noise originating from the photodiodes and the electronic circuits used for signal conditioning. The equation 1 can be recasted as

\[
I(t) = I_{dc}(t) + I_{motion}(t) + I_{pulse}(t) + I_n(t)
\]

where \( I_{dc}(t) \) is a very low frequency offset component. The \( I_{dc}(t) \) is much larger than the fluctuation part \( I_{motion}(t) + I_{pulse}(t) \) and is of no interests for heart rate estimation. The voltage \( x(t) \) which is the result of the PD and current-to-voltage transform after DC removal can be expressed as

\[
x(t) = x_{motion}(t) + x_{pulse}(t) + x_n(t)
\]

The remaining important artifact contribution is thus coming from the movement of the subject. When the subject is not performing any movement, the contribution \( x_{motion}(t) \) is not to be taken into account. Using motion artefact enhancement algorithm in this case would results in an increase in the stochastic contribution and thus a decrease in the signal-to-noise ratio. The way to avoid this situation is to detect the type of activity of the subject is performing. We use two classes of activity: static (S) and nonstatic (NS). The next section consider the problem of automatic classification of activity and motion compensation.

4 Motion classification and compensation

Motion classification is performed on the two dimensional acceleration signals \( a \) based on extracted features. In [7], the features were eigenvalues of the autocovariance matrix of the signals, and the classifier was based on a Hidden Markov Model. In this work, the considered features are the averaged spectral entropy \( H_S(k) \) and the energy \( E(k) \) of the 4th-acceleration signal over a sliding window.

Thresholding on the energy levels unable us to specify the class \( S \), i.e. \( max_k \{ E(k) \} \leq E_T \) where \( E_T \) is a predefined threshold. Whenever \( max_k \{ H_S(k) \} \leq H_T \) (\( H_T \) is a predefined threshold) and \( max_k \{ E(k) \} \geq E_T \), we have detected the class \( S \), and the signals are then further processed. Figure 3 shows an example of activity classification.

Once the classification has been performed, signal enhancement can be applied to the signal \( x(t) \). The assumption of a time-varying linear relationship between \( a(t) \) and...
Figure 3. Example of acceleration signals together with corresponding spectral entropies. The color bars indicated the class of activity: $S$ (dark grey), $NS$ (light grey, black, white).

$x(t)$ is used in this work. In order to remove $x_{motion}(t)$ from $x(t)$, we used an adaptive noise canceller [6] with the signals $a$ used as reference. The normalized LMS was used here because of its reduced complexity. After motion artefact cancelling, further cleaning of the signal using principal component analysis have been applied (see figure 2).

Figure 4 shows the result of motion cancellation. The classes $S$ and $NS$ are marked under the figure 4(b) in gray and white respectively. The resulting cleaned optical signal $x_c(t)$ is then processed for heart rate estimation.

Figure 4. Spectrograms of $x(t)$ (a) and $x_c(t)$ (b) together with the two classes $S$ (gray) and $NS$ (white).

5 Heart rate estimation

Heart rate estimation is based on Maximum A Posteriori likelihood of the clustered inter-beat intervals detected from the signal $x_c(t)$ [4, 8]. Inter-beat intervals are detected using maxima localization over the sliding window. Thresholding on the signal allows to remove local maxima and thus increase the robustness of the histogram clustering. Figure 5 shows an example of heart rate estimation using our approach, and compare it to the Polar estimates. The two curves are very similar and a root mean square error of 5 bpm is reported. Further validation of the approach on a large database of subject and activity conditions is under way.

Figure 5. Heart rate estimation example based on the signals from figure 4(b). The bold dashed line correspond to the Polar estimate, and the thin solid line to our estimates which has been smoothed using an averaging over 15 s.

6 Conclusions

We have proposed an ear located heart rate estimation device using an infrared LED probe. Due to the mechanical properties of the sensor placement in the earphone, a relatively high signal-to-noise ratio can be achieved when the head motion is slow. In other conditions, signal enhancement together with activity classification using acceleration signals have shown a great potential and reliability. Also, the probabilistic approach for the heart rate estimation have shown good results. Commercialization of this device is currently planned.

References


