Feasibility Study of Heartbeat Detection from Optical Interferometric Signal by using Convolution Kernel Compensation

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Abstract: In this paper, a feasibility of detecting heartbeat from optical interferometric signal by using convolution kernel compensation (CKC) latent variable analysis (LVA) approach is examined. Optical interferometer is a very sensitive device that detects physical elongation of the optical fibre. When used as bed or body sensor, mechanical and audible activity of the heart produce perturbations in the detected signal that, when extracted by LVA, allows completely unobtrusive monitoring of heartbeat. We performed an experiment with fourteen young healthy participants. They exercised on a cycle ergometer until they reached their submaximal heart rate (85 % of maximal heart rate). During resting period after the exercise optical interferometric signal was acquired along with the referential ECG signal. CKC-based decomposition of 1-minute-long signal segments was performed. The obtained efficiency (sensitivity of 97.8 ± 3.0 %, precision of 93.6 ± 7.6 %) and accuracy (reference-to-detected beat delay of 167 ± 65 ms) are within acceptable limits indicating that unobtrusive heartbeat detection using the proposed approach is feasible.

1 INTRODUCTION

Classical heartbeat monitoring approaches, such as electrocardiography (ECG) and plethysmography require trained physician and controlled clinical environment to perform measurements with a number of sensors and electrodes. This procedure can be uncomfortable, disturbing and impractical for both the patient and physician. In contrast, methodologies for unobtrusive monitoring of heartbeat deploy different types of sensors that can detect electrical, audible or mechanical heart activity, even when there is no direct contact between the sensor and person's body. A short survey of such methodologies is given in (Šprager and Zazula, 2012).

Monitoring of heartbeat by using optical interferometer has already been examined in (Šprager et al., 2010); (Šprager et al., 2011); (Šprager et al., 2012). However, all published approaches are based on linear processing of a single interferometric signal (single-input-single-output system - SISO). By applying nonlinear transforms to an interferometric signal, additional information may be emphasised. Taking such signal transforms as additional observations in parallel with the original single-channel signal, i.e., by forming multiple-input-multiple-output (MIMO) system, multichannel decomposition methods become applicable. The aforementioned signal extension has already been proposed in (Šprager et al., 2012), where a new approach for heartbeat detection from extended interferometric signal has been introduced by computing so called activity index of multi-channel interferometric signal (Šprager et al., 2012). However, activity index only calculates the Mahalanobis distance between the detected interferometer patterns and does not extract the investigated phenomena, i.e, perturbations due to the heartbeat, from the measurements.

Recently, LVA has been demonstrated as one of the most promising tools to analyse multichannel compound signals, including nonlinear instantaneous and convolutive mixtures. In this study, we experimented with previously published CKC decomposition approach that has demonstrated its great capability in decomposing multichannel surface electromyographic signals into constituent motor unit action potential trains (Holobar et al., 2009). However, this approach has never been

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applied to nonlinear instantaneous mixtures of interferometric signals.

The manuscript begins with a description data model and methodology in Section 2. Section 3 explains experimental protocol and evaluates the obtained results. Discussion and conclusions are made in Section 5.

2 METHODOLOGY

2.1 Data Model

Optical interferometry is a well-known principle of measuring external stimuli that triggers changes of optical-fibre length (Udd, 1991). Due to their high sensitivity, such sensors can detect micrometric or even nanometric changes. As a result, tiny variations of pressure against optical fibre generate high changes in optical interferometric signal.

The use of optical interferometer for heartbeat monitoring has already been demonstrated in (Šprager et al., 2010); (Šprager et al., 2011); (Šprager et al., 2012). When in direct or indirect contact with a subject, mechanical or audible activity of myocardium causes perturbations in interferometric signal $i(n)$.

In this study, the Michelson optical interferometer was used combined with laser diode as an optical source emitting the light with the wavelength of 1300 nm. This interferometer has a cosine transfer characteristics with one period corresponding to the fibre length change that is equivalent to the half wavelength of the optical source.

When using optical interferometer for heartbeat monitoring, we observe minute changes of the sensing fibre length, caused by heartbeats $s(n)$ along with all other impacts on fibre elongation $\varphi(n)$, i.e. noise from the environment, thermal drift, etc:

$$i(n) = A(n)\cos\left[s(n)+\varphi(n)\right] \tag{1}$$

Analytic representation of $i(n)$ can be obtained by using Hilbert transform:

$$\begin{aligned} x(n) &= i(n) + j\cdot H\left[i(n)\right] = \\ &= A(n)\Big[\cos\left[s(n)+\varphi(n)\right] + j\cdot\sin\left[s(n)+\varphi(n)\right]\Big] \end{aligned} \tag{2}$$

where j stands for imaginary unit and $H[.]$ for the Hilbert transform. The phase angle of analytic signal $x(n)$ can be expressed from (2) as

$$\tan\phi(n) = \frac{\sin\left[s(n)+\varphi(n)\right]}{\cos\left[s(n)+\varphi(n)\right]} = \tan\left[s(n)+\varphi(n)\right] \tag{3}$$

Thus,

$$\phi(n) = s(n) + \varphi(n) = \tan^{-1}\left[x(n)\right] \tag{4}$$

When impact of noise and movement artefacts $\varphi(n)$ is negligibly small, (4) evolves into:

$$\phi(n) \approx s(n) \tag{5}$$

Therefore, signal $s(n)$ is obtained by computing $\tan^{-1}\left[x(n)\right]$. The latter produces wrapped phase $\phi(n)$ that must be unwrapped for further decomposition needs.

2.2 Decomposition of Demodulated Interferometric Signal by CKC

Multichannel CKC is suitable for decomposition of linear mixtures of signals comprising finite-length symbols (Holobar and Zazula, 2007). The observed symbols are first modelled as channel responses in a MIMO system, while the channel inputs are conceptually considered sparse positive pulse trains (PTs) carrying the information about the symbol arising times. As demonstrated in (Šprager and Zazula, 2012), in heartbeat observations, the large portion of repeating symbols corresponds to fibre-optic responses to the heartbeats.

Fibre-optic observation $s(n)$ is a single-channel signal. As such, it is not suitable for the CKC processing and needs to be transformed to multiple observations. The latter can be achieved by nonlinear operation, such as by using Hadamard entrywise products of $s(n)$ for different lags l.

For each $m = 1,\ldots,M$ and all possible combinations of lags $l_i = \{0,\ldots,L\}$, i=1,…,m, the entrywise product $s(n-l_1)\otimes\ldots\otimes s(n-l_m)$ is calculated between the m lagged versions of $s(n)$. Obtained set of signals is denoted with $\mathbf{s}_{M,L}(n)$. This nonlinear extension of single-channel observation enhances the non-overlapped signal components (Istenič and Zazula, 2010).

In the following step, CKC-based decomposition method is applied to signal $\mathbf{s}_{M,L}(n)$. Outputs from the CKC decomposition are reconstructed PTs that indicate symbol arising times.

Fig. 1.a shows three individual heartbeats as detected by three different PTs (depicted by black asterisks, blue crosses, and green circles) along with referential ECG signal drawn in red. It is evident that a single heartbeat was decomposed into three different symbols. We assume that these symbols are consequence of different contributions in interferometric signal due to mechanical and audible

myocardium activity (Šprager and Zazula, 2012). However, in multivariate observations $\mathbf{s}_{M,L}(n)$, new symbols can also be generated by aforementioned nonlinear extension of single observation $s(n)$.

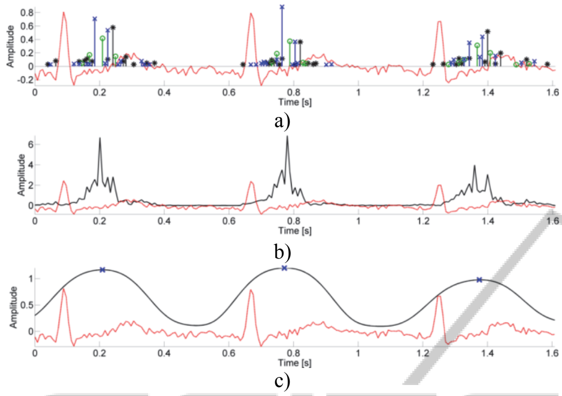


Figure 1: Heartbeat detection using CKC method: (a) Three pulse trains (PTs) obtained by the CKC method are depicted by asterisks, crosses, and circles; (b) marginal energy of PTs in 1.a over time; (c) smoothed version of signal from 1.b by using local regression with weighted linear least squares. Detected heartbeats are denoted as local maxima. Referential ECG is depicted in all the three panels.

Fig. 1.a confirms that the pulses from the same PT more or less occur at the same time instant after referential R waves (see pulse sequence of different colours for each of three heartbeats). Fig. 1.b shows marginal energy of PTs over time, underpinning the locations where pulses concentrate and point out individual heartbeats. From this point of view, the heartbeat detection step is trivial. The heartbeat time instants can be estimated as local maxima of marginal energy of PTs over time.

In this study, the PT marginal energy was additionally smoothed by local regression using weighted linear least squares with window length corresponding to the highest expected heart rate, i.e. 120 beats per minute (Fig. 1.c).

3 EXPERIMENTS AND RESULTS

The proposed method was applied to the signal set obtained by experimental protocol described in (Šprager and Zazula, 2012). The experiment involved 14 subjects, 11 males and 3 females (age of 30 ± 9 years, height of 176 ± 6 cm, and weight of 77 ± 15 kg), and was performed on a bed with inserted 6 m long optical fibre. Referential ECG signal was acquired with four electrodes firmly attached to the subject's extremities. ECG lead II was taken as the referential one. Each of the observed persons was asked to cycle an ergometer until their submaximal heart rate (85 % of maximal heart rate, which computes as 220-age) was achieved. Afterwards, subjects immediately lied down on the mattress (in the supine position) and were asked to lie still during 4 minutes long acquisition of interferometric and referential ECG signals. With such a protocol, gradual change of heart rate was obtained, which exposed the detection approach to an aggravated situation.

Signals were acquired by costume made four-channel sampling device and digitised by a 12-bit A/D converter built in the microcontroller PIC18F4458. Interferometric signals were sampled at 50 kHz, whereas the referential ECG signals were sampled at 196 Hz. The two signal sequences were synchronized by hardware. It has been shown (Šprager and Zazula, 2012) that, in demodulated signal, the energy of heartbeat contributions due to mechanical and audible activity of myocardium is below 60 Hz. Therefore, after frequency demodulation of interferometric signal, all signals were down-sampled to 125 Hz.

Recorded signals were divided into four one-minute-long segments. Each segment was then nonlinearly extended by using entrywise products up to the 5th order (M = 5) with lags up to L = 10 samples and decomposed by CKC decomposition approach (Holobar and Zazula, 2007).

The acquired referential ECG signals were used to validate the efficiency and accuracy of the proposed approach. The validation step was based on the R waves in the ECG signal as automatically detected by the method published in (Pan and Tompkins, 1985).

Detection efficiency was determined according to each referential R wave. Due to delays of mechanical activity of the heart in comparison with the ECG signal, the heartbeats detected from the interferometric signal fall between two consecutive referential R waves. In the ideal case, exactly one detected heartbeat appears in every RR interval. In this way, all detected heartbeats can be grouped in the following three classes:

- true positive (TP) – the number of first detected heartbeats in the RR intervals,
- false positive (FP) – the number of all detected heartbeats in RR intervals, excluding the first heartbeat in each RR interval,
- false negative (FN) – the number of all undetected heartbeats in RR intervals.

With these classes, sensitivity (r_s) and precision (r_p) were calculated as follows:

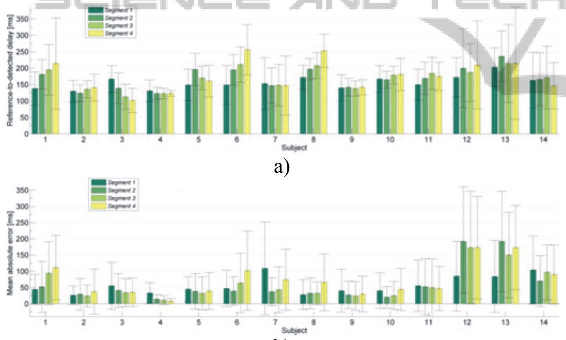
$$r_s = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}} \quad \text{and} \quad r_p = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}} \qquad (6)$$

Overall sensitivity and precision for all 14 tested persons yielded 97.8 ± 3.0 % and 93.6 ± 7.6 %, respectively.

As accuracy metrics, the reference-to-detected heartbeat delays and the mean absolute error between the length of RR intervals and the distance between two consecutively detected heartbeats were calculated. The stability of both metrics was assessed by calculating their standard deviation.

The measured reference-to-detected heartbeat delays for all subjects are shown in Fig. 2.a. When averaged over all the participants, the overall reference-to-detected delay yielded 167 ± 65 ms. Mean absolute errors are shown in Fig. 2.b. The overall mean absolute error was 79 ± 57 ms.

When measured on a standard personal computer with 2.4 GHz 4-core Intel processor and 8 GB of memory, the average processing time for one-minute-long segment was 10.1 ±1.2 s.



a)

b)

Figure 2: Accuracy metrics for the proposed method obtained from 14 participants: (a) reference-to detected delay; (b) mean absolute error (vertical lines indicate standard deviations).

4 DISCUSSION AND CONCLUSIONS

Efficiency metrics for 14 subjects (Fig. 2) show that heartbeat detection is feasible with the proposed method. Nevertheless, in comparison to more advanced methods (Šprager and Zazula, 2012), obtained results indicate lower efficiency (precision of 93.6 ± 7.6 %) as well as lower accuracy. This also contributes to relative high overall variability of detected heartbeat delays (±65 ms) and relatively high mean absolute error in estimated inter-beat interval lengths (79 ± 57 ms). The reason probably lies in relatively high amount of symbols/PTs comprising the multichannel observations $\mathbf{s}_{M,L}(n)$. While a significant portion of them reflect responses to heartbeats, the other reflect the repeating interferences from outer world (e.g., due to breathing, movements etc.) This is also the main reason why our heartbeat detection was not made dependent on single pulses in PTs, but was based on observation of group of pulses as obtained by calculating marginal energy of all PTs.

Accuracy of heartbeat detection is additionally degraded by smoothing operation presented in Fig. 1.c. To avoid smoothing, the detection step should focus on the individual PT and select only those that represent the actual heartbeats. This is not a trivial task. Thus, further research of interferometric signal properties, their nonlinear extensions and their CKC-based decomposition is required.

The sampling frequency of demodulated interferometric signal used in the proposed method was set to 125 Hz, which is four times lower than in similar approaches (Šprager and Zazula, 2012, Šprager et al., 2010, Šprager et al, 2011, Šprager et al., 2012). This is not a limitation as the down-sampled interferometric signal still preserves all spectral energy of components induced by mechanical and audible activity of myocardium (Šprager and Zazula, 2012). The selected sampling frequency was also low enough to guarantee acceptable decomposition time – about 10 s for 60-second-long signals.

Considering chosen segment length of interferometric signal, it must be emphasised that CKC decomposition relies on statistical signal properties. This means that the signals must be long enough to contain adequately high number of symbol repetitions. One-minute-long segments turned out to be long enough for our decomposition purposes, but hindered the tracking of heartbeats in real-time. The real-time version of CKC method is currently under development and is yet to be tested on interferometric signals.

Finally, it would be interesting to use the proposed method with multi-array sensors that, in contrast to the optical sensor proposed in this paper, produce multiple observations.

In conclusion, method for heartbeat detection using decomposition approach based on convolution kernel compensation has been introduced. Although the efficiency and accuracy are slightly lower than in similar detection methods, the obtained results show great potential in unobtrusive heart rate measurements. The proposed approach also opens a new way of decomposing fibre-optic interferometric signals.

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