Alignment of Multi-Sensored Data: Adjustment of Sampling Frequencies and Time Shifts

Marcus Vollmer[1,2], Dominic Bläsing[3], Lars Kaderali[1,2]

[1] Institute of Bioinformatics, University Medicine Greifswald, Germany
[2] German Centre for Cardiovascular Research (DZHK), Greifswald, Germany
[3] Institute of Psychology, University of Greifswald, Germany

Abstract

Objectives: *For a more comprehensive clinical picture, measuring vital signs with multiple devices is advantageous due to the acquisition of complementary information (ECG, body movement, temperature and respiration) and the possible compensation of signal loss. Our aim is to find a robust way for the correction of sampling frequencies and the alignment of non-synchronized sensors.*

Methods: *We used data from an experiment including five different devices, which simultaneously measured the activity of the heart and other vital parameters (Hexoskin Hx1 Smart Shirt, SOMNOtouch NIBP, Polar RS800 Multi, eMotion Faros* $360°$*, NeXus-10 MKII). Our alignment procedure is based on pairwise comparisons of 300 consecutive heart beat intervals to the Hexoskin reference interval sequence, using minimization of the overall absolute sum of differences for alignment. Robust linear regression fits were used to adjust for general deviations in the sampling frequencies and for non-linear resampling in a sliding window.*

Results: *Altering sampling frequencies were identified in Faros and Polar devices in the course of experimental measurements in all of 13 subjects. SOMNOtouch and NeXus had the lowest standard deviation across all subjects. In two identical Faros devices, the average sampling frequency was* $+0.0293\%$ *and* $+0.0175\%$*.*

1. Introduction

Tracking heart activity via ECG is standard in research and in daily hospital routine. The invention and development of smaller sensor technology facilitates the collection of ECG data without sacrificing quality. Measuring heart rate variability (HRV) is one way to objectify stress via physiological data [1]. Therefore a broad range of equipment is used to measure HRV. Chest straps, Holter ECG systems, even sensor-equipped shirts and smart watches are used. As a consequence, instruments appear in different shapes, sizes, numbers of electrodes and different sampling frequencies. Comparability of data acquired with different platforms thus becomes an issue. Numerous algorithms for data fusion exist to increase robustness, see [2]. Some algorithms utilize simple cross correlations, while others utilize neuronal networks to solve the data fusion problem. Difficulties arise from the imperfection and diversity of sensor technology, outliers, spurious data, operational timing and data alignment/sensor management [2, 3]. Data alignment seems to be a common problem in spectral analysis, chromatography, NMR spectroscopy and similar fields [4–6]. For physiological ExG data (such as ECG, EEG, EMG, EOG) there are some further aspects that need special consideration. Significant problems are noisy measurements due to body movement, muscle activity or overlapping of signals. As a result of using different sensor technologies, placement and instruments, the amplitude and morphology of the ECG signal varies between instruments. Another big problem might be preprocessed data and artefact correction, or the appearance of measurement artifacts that could result in missing data, such as "out of sequence" measurements [2].

The aim of our study was to measure the validity of various ECG measurement systems in the field. We therefore collected data from subjects wearing various instruments simultaneously, to allow a direct comparison of measurements. Each instrument had its own sampling frequency and the recording cannot be started simultaneously. The aim of this paper is to demonstrate a workflow in which ECG data can be sufficiently aligned through non-linear resampling to get an extensive data set of all measured features (including secondary features like acceleration, temperature, and respiration). To reach the goal of our study it is not necessary to fuse multiple different data streams into one, but the main challenge is to properly align them based on the common heart beat measurement. Even though in our study the correlation between the different sensor techniques should be close to 1 (because measurements are done in the same person for each instrument), it might be difficult to use simple cross-correlation algorithms like

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correlation optimized warping (COW) [5] or automatic time-shift alignment (ASTA) [7] to align the data. A reason to refrain from correlation-based alignment methods is substantiated by different morphology across the ECG leads due to different sensor placements. In particular the most prominent characteristic in ECG signals, the QRS complex, is contributing fewer values to the computation of cross-correlations due to its fast duration compared to the T wave or inter-beat segments. Morphology disagreements in these subordinate characteristics would dominate the cross-correlation and hence would bias the alignment. We therefore rely on a simple and robust procedure making use of beat-to-beat intervals (RR intervals), described in the following.

2. Experiment description

Study design Seven female and six male volunteers participated in this study. Written informed consent was obained from all participants and the study was approved by the ethics committee of the University of Greifswald (Identifier: BB 171/17). After applying all five instruments (starting with the adhesive electrodes, finishing with the Hexoskin shirt) as illustrated in Figure 1, participants took place on the treadmill and got secured. After a short instruction a $5\,\mathrm{min}$ baseline measurement in standing rest was followed by $5\,\mathrm{min}$ walking at a constant pace of $1.2\,\mathrm{m/s}$. Equipped with a backpack and headphones, the third part of the experiment was a $5\,\mathrm{min}$ cognitive task. The participants were asked to vocalize a shifted sequence of numbers starting with the first number when the third number was played (auditory 2-back paradigm, see [8]). The last part of the study was a physical exercise, walking $5\,\mathrm{min}$ on the treadmill with $1.2\,\mathrm{m/s}$ and a $15\,\%$ gradient. Between the different phases, participants were asked to answer the NASA Task Load Index to measure individual strain [9]. To sample the start of each phase a trigger point was set using eMotion Faros 360°.

3. Data processing

Preprocessing Preprocessing and data analysis were conducted using Matlab R2019a. We imported the signals with header information from raw and processed output files (wav files of Hexoskin export, hrm file for Polar watch, EDF files otherwise) and stored the data in a structured array. First, we applied a moving average filter to the ECGs for downsampling. For baseline removal, we applied a $25\,\%$-trimmed mean filter with a window size of $200\,\mathrm{ms}$, which acts as a high-pass filter. Next, standardization transformed the signals to a unit-less signal. After annotation of the hear beat using an open source heart beat detector [10][1], we searched for the R peak in the immediate surrounding of the raw signal to compensate for the uncertainty from downsampling. We computed RR intervals for each signal respectively. After that, intervals suspected to be adjacent to irregular heart beats or unreasonable intervals in noisy segments were removed from the interval sequence by `NaN`-replacement. This was done using a filtering method based on relative RR intervals [11].

Furthermore, we discovered a wrong sampling frequency ($8000\,\mathrm{Hz}$ instead of $8192\,\mathrm{Hz}$) stored in the EDF files of our Nexus device, which we corrected manually and before the following alignment task. We also identified wrong artificial RR intervals in the Polar recordings. These offsets within the RR interval sequence were also corrected in advance.

Alignment of multi-sensored data Hexoskin's ECG was used as the reference ECG channel to which all other sensors were aligned to (chosen after manual screening of signal quality and first analysis of sampling frequency constancy). We performed the alignment of RR interval sequences by searching for the best local alignment of a short segment of 300 beats from a resting state period (the sequence with the lowest heart rate). We then searched for a time shift d for which s, the mean absolute difference to the reference annotation, reached its minimum value. We took into account that some of the heart beats could be misplaced due to noise, or could not be identified at all.

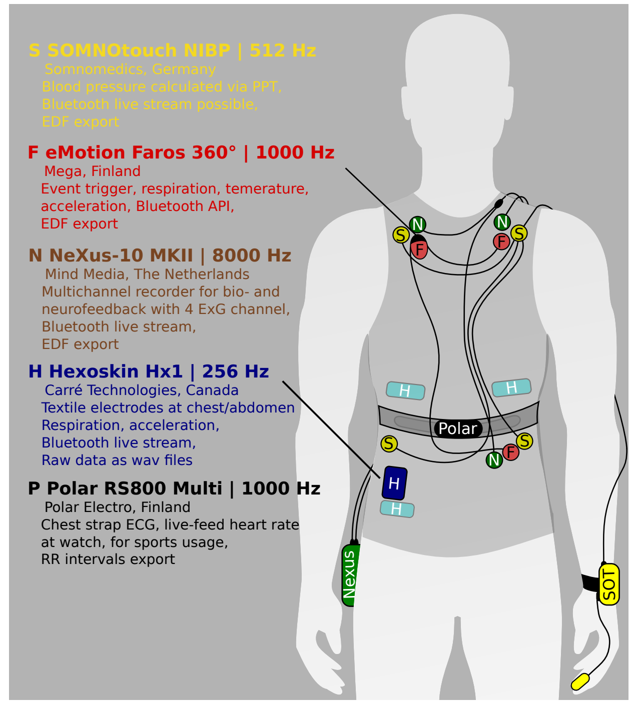

Figure 1. Illustration of sensor placement and specifications of five recording devices: Hexoskin Hx1 Smart Shirt, SOMNOtouch NIBP, Polar RS800 Multi, eMotion Faros 360°, NeXus-10 MKII. Body silhouette designed by Freepik.

[1] Available via `https://github.com/MarcusVollmer/HRV/blob/master/singleqrs.m`

Therefore, s is based only on matched beats which differ not more than $300\,\mathrm{ms}$. To speed up the process of finding the exact value, our search was divided into two parts. First, we identified a rough estimate of d by finding the best sequence alignment matching the first beat of the reference sequence to any beat of the second RR interval sequence in the way that almost all following beats had an appropriate match. In a second step we refined d by adding small values between $-100\,\mathrm{ms}$ and $100\,\mathrm{ms}$ to adjust for the case, that the first beat does not accurately match the aligned beat from another signal.

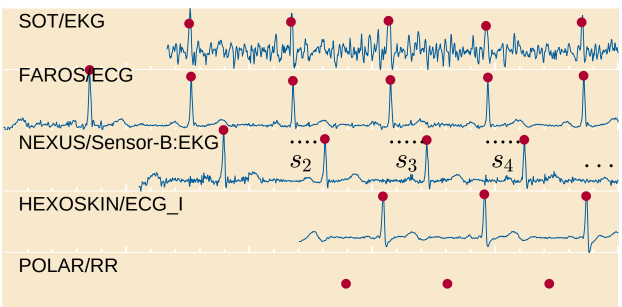

Figure 2. The delay d to align sensors is defined by finding the minimum of the sum of absolute pairwise differences s_i for a pair of beat annotation sequences.

Linear correction of sampling frequencies Inaccuracy in given sampling frequencies may result in linear drifts of pairwise differences of aligned heart beats, see Figure 3. We therefore corrected the sampling frequency of the second sensor. This was done by computing the slope of a robust linear regression fit (iteratively reweighted least squares with a bisquare weighting function) from the 300 matched beats of the resting period. Next, we transformed the resulting slope b into a constant factor for persistent adjustment of the sample frequency:

$$\hat{f}_s = f_s \cdot (1 - b) \tag{1}$$

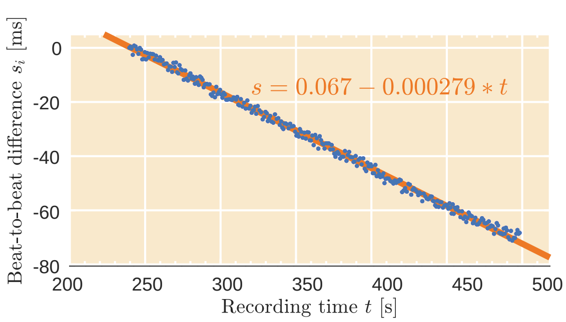

Figure 3. Inaccurate sampling frequencies can be corrected by using the slope of a robust regression fit of Pairwise differences of annotations s_i.

Non-linear correction of sampling frequencies The first aligned signal matrix was generated by applying time shift d and the resampling of the signals using $\hat{f}_s$. Next, we performed a manual annotation of all R peaks for the reference sensor given the credibility from all other aligned ECGs. Based on the manual annotation, we then continued with a non-linear resampling process by computing continuous beat-to-beat differences between the RR interval sequences as illustrated in Figure 4. We assumed that the sampling frequency from built-in frequency transmitters of the recording devices are only capable to vary slowly (depending on temperature changes and the battery level). Consequently, we excluded outliers through moving median and performed a robust quadratic regression to identify local changes in the sampling frequency. The smooth curve of beat-to-beat-differences was interpolated to get a sample-based corrective value to adjust for the local frequency (red line). Finally, these values were used to correct the x-values of the ECG time series and served as input coordinates to linearly resample all signals of a device to the reference frequency of $256\,\mathrm{Hz}$. We computed the minimum, maximum, average and standard deviation of actual persistent sampling frequencies among all participants for comparison with the manufacturers' specifications and checked visually for time-varying changes.

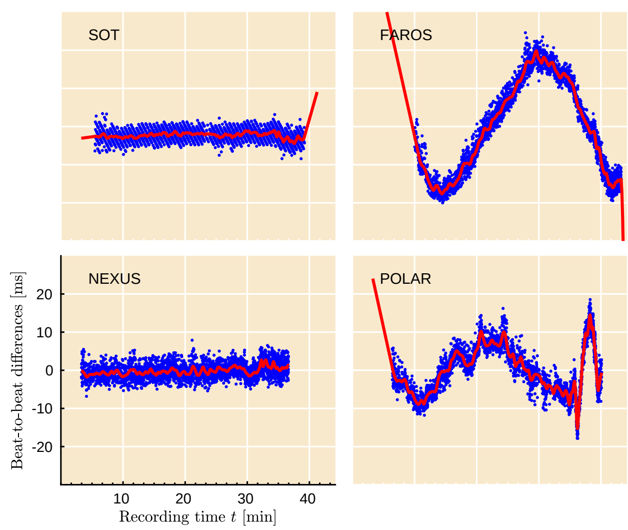

Figure 4. Pairwise differences of beat locations after linear correction. Polar and Faros had inconstant f_s and was corrected by using a robust regression fit (red lines) for resampling.

4. Results

We included 13 participants in our study. We adjusted and investigated variations in sampling frequencies pairwisely as described above. The robust regression fit as shown in Figure 4 quantifies heterogeneous f_s in Polar and Faros devices. In this recording of a subject, beat-to-beat differences start with a $20\,\mathrm{ms}$ delay, decline towards $0\,\mathrm{ms}$, rise to $30\,\mathrm{ms}$ and drop down below zero until the end of the experiment. We observed such behavior, but in different non-linear ways, in all of our 13 recordings. In case of the Polar device, we observed a drift of the pairwise differences especially at the stage of walking five minutes on the treadmill with a $15\,\%$ gradient. Table 1 shows the actual sampling frequencies among all 13 subjects when using Hexoskin's ECG sensor as the reference sensor. Faros and Polar showed the highest spread across the whole experiment. The clinical devices SOT and NeXus showed a fixed correction factor across 13 subjects, speaking of a stable and precise frequency transmitter.

Table 1. Manufacturer's specifications and actual sampling frequency (Hexoskin assumed to be have precise f_s). Two Faros' devices in use, $\hat{f}_s$ splitted according to device ID.

Recording Device	f_s	Mean $\hat{f}_s$ (min to max)	
SOT NIBP	512	511.97	(511.97,511.97)
Faros 360°, ID1	1000	1000.29	(1000.19,1000.36)
Faros 360°, ID2	1000	1000.18	(1000.15,1000.21)
NeXus-10 MKII	8000	7999.67	(7999.67,7999.68)
Polar RS800 Multi	1000	999.91	(999.87, 999.95)

5. Discussion & Conclusions

The incorporation of multiple devices measuring the same entity allows self-verification, increases credibility, and increases resolution of experimental data. Other advantages are the increased range and variety of different sensors, measured at different body positions, in different quality, and resolutions. We used ECG sensors of each device to carry out the correction of time shifts and non-linear adjustment of sampling frequencies on the basis of RR intervals. For Polar and Faros, we have revealed varying sampling frequencies for which we have no sound reason. According to the eMotion Faros series manual 2.3.0, Faros "is suitable for use in an electromagnetic environment" with a recommended safety distance of $1.2\,\mathrm{m}$ to portable and mobile radio sets. In our experiment, Faros was nearby Hexoskin and Polar devices, sending continuously in-time measurements via Bluetooth, which might violate the recommended safety distance. Devices for medical usage (Nexus, SOT) showed more precise sampling frequencies than other devices primary made for personal use (Hexoskin, Faros, Polar). Inaccurate and varying sampling frequencies can have a severe impact in particular in long-term measurements. A change of only $0.01\,\mathrm{Hz}$ would result in a measurement delay of $70.3\,\mathrm{ms}$ after $30\,'$ of measurement. This is even more serious in experimental setups, when the time of events (e.g. induced events, visual perception, drug intake) are tracked simultaneously with different devices.

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Address for correspondence:

Marcus Vollmer / marcus.vollmer@uni-greifswald.de
Institute of Bioinformatics / University Medicine Greifswald
Felix-Hausdorff-Str. 8 / 17475 Greifswald / Germany