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Improvement of Stroke Volume Estimation with Bioimpedance Measurement by LSTM Network Approach Based on ECG during Ergometry

Abstract: Stroke volume (SV) and cardiac output (CO) estimations with non-invasive approaches like thoracic electrical bioimpedance (TEB) measurement become state of the art in clinical practice. Despite the advantages like low costs, low risk of infection and relatively easy application, there are also disadvantages like the sensitivity to movement artifacts and, electrode displacement mistakes. The bioimpedance signal acquired with a tetrapolar measurement has a relatively weak signal strength compared with another common recorded signal, e.g., the electrocardiogram (ECG). For reconstruction and filtering of the dZ/dt signal, different approaches exist like ensemble averaging (EA), scaled fourier linear combiner (SFLC), wavelet denoising and adaptive filter. We propose an artificial neural network with long short-term memory (LSTM) layer for signal reconstruction during ergometry. The LSTM network performs well compared with other algorithms, e.g., with better amplitude (C point) reconstruction. The SV estimation with the LSTM network was at least comparable or even better than the estimation based on SFLC.

Keywords: Bioimpedance, Neural Network, SFLC, Ensemble Averaging, Stroke Volume, Cardiac Output, LSTM network

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1 Introduction

Stroke volume (SV) and cardiac output (CO) determination

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are commonly used in clinical practice for the estimation of the cardiovascular status of patients. CO is the product of SV and heart rate. While it is ordinary to determine the heart rate of a patient, e.g., with an ECG, it is challenging to determine the SV of a patient, especially for every heartbeat. Some approaches exist to calculate the SV including thermodilution, transoesophageal doppler, and the Fick-method to mention just some of them [1]. Many of these approaches are invasive, cost-intensive or at least not capable to estimate SV beat-to-beat. Transthoracic electrical bioimpedance (TEB) overcomes these disadvantages at the cost of some approach-own limitations. The main challenges are movement artifacts, which are the topic of this paper, the maximum injected current passing the descending aorta and reliable and robust electrode placement. These topics were investigated in previous works [2] and [3].

TEB measurement, also known as impedance cardiography (ICG) becomes state of the art in clinical practice. Generally, an amplitude constant current with a fixed frequency in a range of 20 kHz to 100 kHz is applied to the subject with a tetrapolar electrode configuration. The disposable outer electrodes are used for current injection, while the inner electrodes are used for measuring the voltage drop on the surface. The bioimpedance has a constant part, due to the tissue resistance, and two alternating parts. One of these alternating parts is the result of respiration, whereas the other part is a result of the cardiac activity (simplified model). Additionally, the cardiac related part is a result of the windkessel-effect as well as the orientation of the erythrocytes and blood acceleration during a heartbeat. Different approaches exist to filter or estimate the bioimpedance signal and to calculate the SV. Adaptive filters are used [4] to cancel noise. They work well with noisy signals, but not very well with artifacts. Furthermore, ensemble averaging (EA) is used. This approach averages a predefined number of beats. Noise and artifacts are reduced but also blurred. The dynamic depends on the number of used samples. More samples reduce the disturbances but lower the dynamic [5]. The wavelet transformation is also used for denoising and baseline wander removal [6]. Other

approaches are sensor fusion, where, e.g., 2 signals are merged and the scaled fourier linear combiner (SFLC) [7].

2 Methods

For our own setup, we used a current with 2 mA_{RMS} amplitude at 50 kHz. The electrodes were placed from superior to inferior alphanumerical ordered as follows. The electrode A was placed 5 cm above the onset of the neck, the electrode B was placed on the onset of the neck, the electrode C was placed on the level of the xiphoid and the electrode D was placed 10 cm below electrode C. All electrodes were placed on the left side of the patient. Electrode B and C was also placed on the right side (see Figure 1). The voltage drops from electrode B_2 to electrode C_1 and from B_1 to C_2 were measured and two bioimpedance signals were calculated. Generally, only the electrodes on the left side are placed. For performing and sensor fusion, the bioimpedance signal is measured twice across the thorax. If one shortens the B and C electrodes, the disturbances will be also reduced as with a fusion, but also the ECG signal amplitude. The ECG is measured simultaneously to the bioimpedance signal (from B_2 to C_1).

Figure 1: Electrode Placement.

2.1 Ergometry

Ergometry is used for evaluation of the cardiovascular system status and can indicate arteriosclerosis. During the cardiac stress test on an ergometer, an ECG is recorded. Depending on the morphology of the ECG, especially the S-T path, clinicians can assume arteriosclerosis. The measurement is done on an ergometer for heavy exercise.

This results in movement artifacts. Despite this, the ECG can be recorded, because the signal is relatively strong, compared to other signals (10-100 times larger in amplitude than the bioimpedance signal). It is very challenging to record the bioimpedance signal during such exercise. If it is possible, a new cardiovascular parameter could be established, for example, the slope of the SV during the exercise. The SFLC uses the fundamental frequency of the RR interval and its harmonics to reconstruct the original signal. Depending on the adaptation algorithm and coefficient, this approach results in a very stable signal. These coefficients also determine the dynamic behavior.

2.2 Neural Network

An approach related to the signal processing of the human brain is an artificial neural network. These networks mimic their biological counterpart. In the basic form, data is processed through the network and a learning algorithm (backpropagation) adapts the inner weights of the connections to produce a specific output, e.g., for supervised learning. This approach is part of machine learning. LSTM and deep neural networks are a more specialized form. We use shallow neural networks separately and combine the estimated output of 25 shallow neural networks (multilayer perceptron) for an estimation of the bioimpedance signal. Additionally, we use an LSTM network to predict the bioimpedance signal, based on the ECG signal. All neural networks we used had to predict the current bioimpedance signal based on the last 200 ECG signal samples.

2.3 Procedure

We performed an ergometry measurement with a healthy subject. First, a baseline was recorded for 60 s. Then the subject started to cycle 20 s, stopped for 5 s and cycled again for 15 s, followed by a 5 s break. The 15/5-time interval was performed for 3 minutes. Finally, the subject had to rest for 3 minutes. We recorded an ECG from electrode B_2 to electrode C_1 and two bioimpedance signals from electrode B_2 to electrode C_1 and from electrode B_1 to electrode C_2 . The electrodes A and D were used to inject a 50 kHz current for the bioimpedance measurement. The breaks were included to have a reference during the exercise for the different algorithm for the waveform shape as well as for the calculated SV. Afterward, we processed the bioimpedance signals as follows. We performed a fusion (scaled the auxiliary signal and averaged the original with it) of the two independent measurements (1st comparison signal (CS)) and

calculated from this signal the ensemble averaged version (2nd CS, used 2 beats before and 2 beats after the current signal for reconstruction). An SFLC with least mean squares algorithm was applied to cancel the disturbances (3rd CS). Finally, we created 25 shallow neural networks and one LSTM network with MATLAB. This results in three additional signals. One was processed by the best shallow neural network after training (4th CS), a second was processed by averaging 25 shallow neural network outputs (5th CS) and the last was processed by the LSTM network (6th CS). As training data for the LSTM network, the original signals without the pause intervals were used. The breaks were used as validation data. This was done because simple cross-validation is not possible. The network itself

Figure 2: Original Signal with specific points during break and SV estimation during break.

Figure 3: SV estimation of original and processed

reconstructs only correlated data in the bioimpedance signal based on the ECG. After this, we compared the signal shapes during baseline (start), breaks and recovery (end) phase. Furthermore, we compared reconstruction of correct B

(opening of the aortic valve), C (highest amplitude in the derivative of the bioimpedance signal, $dZ/dt_{\max}$) and X (closure of the aortic valve) points in the bioimpedance signal, which are important for the determination of SV (specific points and SV estimation can be seen in Figure 2 as an example). We used

$$SV = C_P * \sqrt{\frac{dZ}{dt_{\max}} \cdot \frac{LVET}{Z_0 \cdot \sqrt{T_{RR}}}} \quad (1)$$

where C_P is a patient-specific constant (set to 1), $dZ/dt_{\max}$ is the maximum change of the impedance signal, Z_0 is the basal impedance, LVET is the left ventricular ejection time, T_{RR} is the R-R spike interval. The SV was normalized to the baseline phase. Additionally, an inspection of the complete processed signal was performed for each method.

3 Results

A good reconstruction was achieved with the LSTM network. Comparing the complete signals the resulting SV estimation of the LSTM network seems nearly like the estimation done by the SFLC method (Figure 3). The mean square error (MSE) was calculated during the break intervals between processed and original signal from electrode B_2 to C_1 . This can be done because algorithms need time to adapt and will not reproduce the original signal immediately. Moreover, the MSE for the B, C and X points were calculated (Table 1). For B and X point, the time is important, whereas for C points the amplitude has to be correct.

Table 1: MSE of processed signals during short breaks, specific point detection and SV estimation

Signal	MSE Signal [(Ω/s) ²]	MSE B Points [ms ²]	MSE C Points [(Ω/s) ²]	MSE X Points [ms ²]	MSE SV (norm.)
Fusion	0.23	66.89	0.236	67.2	0.0266
Fusion + EA	0.20	45.85	0.242	21.9	0.0101
Single NN	0.66	8.26	0.476	70.7	0.0174
Multiple NN	0.31	30.51	0.466	63.0	0.0239
SFLC	0.75	4.94	0.251	34.3	0.0459
LSTM NN	0.65	9.19	0.227	78.63	0.0182

The LSTM network performs well with the lowest error in C point determination (MES error 0.227 (Ω/s)²) during breaks and a good SV determination (error 2 %). One has to consider that the reconstruction by LSTM wasn't the best during the breaks but it processed a physiological signal also during disturbed phases (compared to fusion and EA).

4 Discussion

It seems that the LSTM network works well for a first trial. The signal parts during the disturbed parts are similar to the SFLC approach and similar to the original signal during the breaks. Some signal peaks can be seen in the SV estimation of the LSTM network as a result of false bioimpedance point detection. During the breaks, the SFLC SV was estimated too high by nearly 5% compared to the original signal, because of the lower dynamic. SFLC also estimated the SV in the baseline phase too high. During the breaks, the LSTM network SV estimation decreases as it does in the reference signal. Compared to SFLC, the LSTM has the additional advantage that it only needs the ECG without R-spike annotation. The presented results are very promising with respect to the strong movement artifacts in the bioimpedance signal. The LSTM network can generate an ECG-to-bioimpedance-signal model that has more dynamic, than the SFLC approach. The SV estimation during the disturbed phases looks similar to the SFLC result. If the generation of such a model is possible, one can assume, that it should also be possible to estimate SV directly from the LSTM network but with a complete signal, sensor fusion can be done with other bioimpedance signals or its surrogates. An averaging of SV can also be done, but one has to consider, that the B, C, and X point detection in the postprocessing works better with an undisturbed signal. For the validation, additional measurements are needed with more test subjects as well as a second run with data not used for the learning process. The most suitable case for the evaluation would be a beat-to-beat SV reference that is difficult to record. Further investigations are needed to evaluate a subject-specific model with other subjects. Pre-trained models should also be considered. Approaches like SFCL and LSTM network offer the possibility of new cardiovascular status parameters like the adaptation rate of SV during exercise (sSV, slope of SV). The simple multilayer perceptron performed bad and may need data alignment and normalization for a better performance.

5 Conclusion

As a first trial, we evaluated a new approach based on an LSTM network for estimate SV for disturbed signals, e.g., as a result of movement artifacts. The estimation error of the SV during reference breaks was small 1.82% (normalized). The LSTM seems to be the best approach compared to others like

SFLC, sensor fusion, shallow neural networks, and ensemble averaging. We assume an LSTM network can learn an ECG to dZ/dt signal (bioimpedance sig.) model with good C point estimation. The B and X point reconstruction needs to be improved. The results look promising but need to be clearly validated with a larger number of subjects and additional measurements. The LSTM network performs similar to the SFLC but with a higher dynamic. It can be used to generate a surrogate signal for sensor fusion, to estimate the SV by averaging or to offer the possibility of new cardiovascular parameters like the slope of SV during exercise.

Author Statement

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