An Online Signal Processing Chain for Respiratory Rate Estimation in Magnetic Induction Measurements

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Abstract. In this paper, an online signal processing chain for extracting respiratory rate from magnetic induction measurements (MIM) is presented. A flexible processing framework is presented and a breath-to-breath estimation as C. Brüser proposed in [1] as a beat-to-beat estimator is implemented within this framework. The measurement device MUSIMITOS2+ is used for test data recording. For this measurement a healthy subject was placed on a sun lounger over a 6(6)-gradiometer. The measurement is analyzed exemplarily. First, simple pre-processing steps are used to prepare the data for a principal component analysis (PCA). The output of this PCA is then used as the input of the interval estimator.

As a first result of this test, one can assume that the respiratory signal could be extracted from the signal via PCA even though some channels contain bad signals. Even though the estimator would benefit from some further improvement in robustness, the interval estimation was successful.

Keywords
Magnetic induction measurements, respiratory rate, interval estimation, online signal processing

1. Introduction

In medical care, many patients benefit from a non-contact measurement of vital signs. Among others, those on the intensive care unit (ICU) as well patients with fragile skin e.g. neonates. These contactless monitoring techniques include, for example capacitive electrocardiography (cECG) and photoplethysmographic imaging (PPGI) [2]. Another promising technology for contactfree measurement of heart and lung activity is magnetic induction measurement (MIM), which is the center of this paper is based.

In this paper an online processing framework is evaluated by constructing a tool chain for breathing interval estimation in MIM. The paper is structured as follows: In Section 2 the ‘Materials and Methods’ a short introduction to MIM is given and the used hardware is introduced. Afterwards the basics of the processing chain are presented. In Section 3 the results are presented with the help of a representative extract of a signal and followed by a short discussion in Section 4.

2. Materials and Methods

The measurement principle of magnetic induction measurement is based on the induction of an eddy current into an object under test with non-zero conductance by an alternating magnetic field, known as the primary field (Fig. 1). These eddy currents will create an alternating magnetic field on their own, known as the secondary field. This secondary field depends mainly on the conductivity distribution of the object under test and can be measured by a set of receiving coils. In case of medical application, the measured signal will give an indication of the bio-impedance of the patient [3]. In analogy to EIT, vital signs can be derived from

![Fig. 1. The basic principle of magnetic induction measurement, showing 1 Tx-coil and 2 Rx-coils](image-url)
the measurement of the bio-impedance [4]. Therefore, it is possible to measure vital signs contact-free with the MIM technology. With a typical wavelength of 30 cm of the primary field and the coils placed a few cm away from the patient, the patient will be in the near field of the coils and propagation delay can be neglected.

2.1. Hardware

For MIM the MUSIMITOS2+-device has been developed in previous work [5]. The transmitting coils (TX) are driven by amplifiers that are controlled by a 10 MHz DDS-source. The signal is received by a two coil antenna and needs to be down-converted to base-band. That is accomplished by IQ-demodulation resulting in real and imaginary part for every channel. The data is digitized in base-band via National-Instrument-ADC-cards. Since the device is able to feed six different sending coils at once, an axial 6(6)-array has six sending and six receiving coils, which can be operated at the same time due to frequency duplexing. The received signals can be distinguished by their slightly different sending frequency, so that the measured secondary field by one receiving coil can be divided into six signals which correspond to the six different sending coils. In the following, 'channel x-y' names the channel where x is the sending and y the receiving coil. The device records $6 \cdot 6 = 36$ complex signals, i.e. 72 sample series which are send to the signal processing application with 2604Hz sample rate resulting in $\approx 187000$ Samples per second. For evaluation the MUSIMITOS2+ is also capable of recording reference data of PPG-sensor and flow sensor.

Measurement coils: Since the primary field is orders of magnitudes higher than the secondary field, a primary field compensation needs to be performed. Therefore, an axial gradiometer setup is chosen. Two receiving coils are placed at the same distance parallel to the sending coil as shown in Fig. 1. If the magnetic flux of the primary field is the same in both coils, influence of the primary field can be compensated by subtracting both voltages. In reality, the coils will be adjusted for every measurement, so that the influence of the primary field is minimized. Nevertheless the effect of the primary field will never be completely eliminated. For long measurements the coils might even detune', so that no useful signal will be received or the signal is contaminated with a high drift. This means that all of the 72 different channels might contain information on the respiratory activity of the subject, but some might not due to subject placement, de-tuned primary field compensation or other induced interference in the coils or signal line. To extract a robust respiratory rate out of this measurement in an online manner, a signal processing has been developed.

2.2. Online Signal Processing

For flexible online processing of sensor data we developed, a framework in C++. This framework is based on signal processing nodes that process incoming data in various ways and can be connected to each other to build a process chain as shown in Fig. 2. Every node saves the output data to its own multi-channel circular output buffer for which each following node is registered as a consumer. Since process paths can be moved to different threads, the buffer takes care of all consumer, so that thread safety is ensured and no premature overwriting can occur. All buffers can be visualized during the processing for deeper analysis.

The first node of a chain should always be a data source which in this case is chosen to be the MUSIMITOS2+. This node handles communication to the device and receives the measurement data via TCP-connection. Since data is fed continuously to the process chain, each node needs to be capable of processing data in small chunks and push data to the next node. For most nodes, the minimal chunk size is set to one sample, so that a continuous flow of single data samples through the process chain is kept. However, there are nodes like the downsampling-node, which will wait for at least a block of the size of the decimation factor. For testing purpose, there is also a playback feature for recorded data as well as a signal-generator-node is included. For further evaluation, a Matlab\(^1\)-export-node is implemented. Due to an easy extension of the signal-source-class, the proposed tool-chain can be used for other measurement devices with only small changes.

The evaluated process chain for the measurement is shown in Fig. 2 and can be divided as follows:

- Pre-Processing (1. - 3.)
- Channel reduction via PCA (4.)
- Breath-to-breath estimation (5.)

Pre-Processing: First of all, the reference signal, which is also recorded on the NI-ADC cards, is excluded from the processing by channel selection and only used for reference.

For the pre-processing steps, typical filter-nodes such as IIR-filters and FIR-filters were implemented. The FIR-filter uses a simple overlap-add method to process the data. Note that even though for every input sample the corresponding output sample is calculated with negligible delay, the filters induces a time shift of $\frac{N}{2}$ due to the nature of causal FIR-Filters. The pre-processing suits two purposes: reducing the data rate and extract the useful signal by reducing out-of-band noise. To reduces data rate, the first step is decimation by factor of 32. This includes a anti-aliasing FIR-Filter with 348 coefficients, $F_{\text{pass}} = 21 \text{ Hz}$ and $F_{\text{stop}} = 40 \text{ Hz}$. Since $348$ is small compared to $F_s = 2604$ the introduced delay

\(^1\)mathworks.com
1. Remove reference signals

2. Input-Signal
   - FIR-Filter LP 21..40Hz
   - Downsample

3. Downsampled Sig
   - FIR-Filter LP 2..5Hz
   - DC-Removal

4. Usefull Signal Extraction
   - FIR-Filter LP 21..40Hz
   - Downsample

5. PCA-Comp
   - 1 Channel 81.375 SPS
   - Extract Respiratory Rate

Fig. 2. The implemented process chain for the online extraction of breathing intervals.

is less than 100 ms. After this filtering, a downsampling to $f_s = 80$ Hz achieved. For possible heart-beat detection, this high sample rate is suitable and will be processed in further work. For the detection of breath cycles, the data is low-pass filtered again. We define the upper and lower frequency of the breathing signal as $T_{\text{max}} = 10$ s and $T_{\text{min}} = 0.5$ s and use an equiripple FIR-Filter with $f_{\text{pass}} = 2$ Hz and $f_{\text{stop}} = 5$ Hz with 68 coefficients.

For processing with PCA and interval estimation, a DC offset is troublesome. To remove the mean without introducing a delay of several seconds, like a FIR-Filter with low cutoff frequency would do, an IIR-Filter is used. The filter has the form

$$H(z) = \frac{1 - z^{-1}}{1 - \alpha z^{-1}}.$$  \hspace{1cm} (1)

A good choice of $\alpha$ has been determined as 0.99 in this setup.

**Principal component analysis:** Principal component analysis (PCA) is used for data and noise reduction. The basic idea is to map the $N$ dimensional input signal onto $N$ principal components via a projection matrix $W$. The first component will have the highest variance and therefore contain most information of the signal course. By neglecting the $I = N - M$ last components of the PCA, the data is reduced to $M$ dimension with minimal information loss in terms of variance. This can be used for data reduction and denoising, if the useful signal is of higher variance than the noise. For fast online processing an iterative algorithm proposed by Y. N. Rao is used [6][7] and implemented in the framework. The PCA is run on all 72 channels and the first component is used for further processing.

**Interval Estimation:** The interval estimation of this setup is based on a beat-to-beat algorithm proposed by C. Brüser in [1] as a robust BCG heart rate estimator. The algorithm was implemented in the framework and used to detect respiratory rate.

First an upper and lower bound for the interval detection is chosen. As previous, we use $T_{\text{min}} = 0.5$ s and $T_{\text{max}} = 10$ s. For every estimation step, a window of the latest $N = 2 \cdot T_{\text{max}} \cdot f_s$ samples is used. For every discrete $T = k \cdot f_s$ between $T_{\text{min}}$ and $T_{\text{max}}$, the likelihood for being the true interval length is calculated. Therefore, three estimators are fused to one probability distribution by multiplying their output. The modified autocorrelation (CORR) is calculated for every window by

$$\text{CORR}(n) = \frac{1}{N} \sum_{i=0}^{N} w[i] w[i-N]$$  \hspace{1cm} (2)

where $N$ denotes the lag in samples and $w$ the extracted window. Instead of a fixed window size, the modified version will sum only over $N$ samples.

**Modified average magnitude difference function (AMDF)** is calculated as follows:

$$\text{AMDF}(n) = \left( \frac{1}{N} \sum_{i=0}^{N} |w[i] - w[i-N]| \right)^{-1}$$  \hspace{1cm} (3)

**Maximum amplitude pairs (MAP)** is taken as

$$\text{MAP}(n) = \max_{i\in[0...N]} (w[i] + w[i-N])$$  \hspace{1cm} (4)

For in detail explanation and analysis of this interval estimator the interested reader is once more referred to the publication of C. Brüser[1].

### 3. Results

In this section, the result of each processing step as described in chapter 2.2 is presented using a representative example. The data was recorded from a healthy subject using a 32-channel 6(6)-gardiometer array. The subject had a distance of about 2 cm to the upper receiving coil and a distance of 5-6 cm to the sending coil. A sequence of normal and faster breathing was performed. To test the approach against partly...
bad signal quality some coils where not tuned properly: The first and fifth coil where let with a strong primary influence while the fourth coil was fully disconnected, hence recording no real data.

The process steps are shown for 1-1, 2-2 and 6-6 which had a good signal quality. A 30 s interval was extracted. In the middle of this interval (55 s), the subject changed the breathing interval from approximately 4 s to 2 s, as shown in the flow signal (see Fig. 3). In Fig. 4 the raw signal for this time period is shown. Since there is a high DC offset, breathing activity can hardly be seen. Thus, a single component is shown in Fig. 5. By comparing this signal to the reference measurement in Fig. 3 one can vaguely identify the respiratory activity. With further processing steps the respiratory signal can be extracted nicely. It is worth noticing that signals might have a different sign, e.g. compared real part 2-2 with its imaginary part (see Fig.6). Notice, the shown signals are the ones with best signal quality to demonstrate the influence of the pre-processing. In the bulk of 72 channels there are a lot of channels that capture few to nothing of the respiratory rate. For automated channel selection and weighting in such a scenario the PCA-based approach was tested. The result are demonstrated in Fig. 7. Notice that the
y-axis of Fig. 7 is upside down, since the sign of the output of the PCA is not defined. The estimated interval can be seen in Fig. 8. The estimated breath cycle time can be derive from the figure. The change in breathing rate at 55 s from 4 s to 2 s is clearly detected. Nevertheless, noticeable artifacts occur in between. However these false detection come along with a lower estimated probability and might be discarded using further data processing.

4. Discussion

In further works, the adaption of the PCA to subject movement as well as changing condition should be analyzed in detail. For the interval estimation, an integration over a short time period, which was also proposed by C. Brüser in [1] should be implemented to reach a higher robustness. At last the estimated probability could be used to detect outliers in interval estimation. Also the breathing signal could be extracted from the signals in a robust manner, further improvement needs to be implemented for a robust interval estimation. Nevertheless, the proposed online signal processing chain shows promising results and the functionality of the developed online signal processing framework has been demonstrated.

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References


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Pascal Vetter was born in Lüdenscheid, Germany in 1987. He finished his Abitur in 2007 and received the B.Sc. and M.Sc. degree from RWTH Aachen University in 2011 and 2014, respectively. He is currently a research associate and Ph.D. student at the Philips Chair for Medical Information Technology, Helmholtz-Institute for Biomedical Engineering at RWTH Aachen University. His research project is based on magnetic induction measurements and covers hardware as well as signal processing for said technology.