Spatial Analysis of Cardiorespiratory Thorax Movement with Motion Capture and Deconvolution

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Abstract. Unobtrusive sensing is a growing aspect in the field of biomedical engineering. While many modalities exist, a large fraction of methods ultimately relies on the analysis of thoracic movement. To quantify cardiorespiratory induced thorax movement with spatial resolution, an approach using high-performance motion capture, electrocardiography and deconvolution is presented. In three healthy adults, motion amplitudes are estimated that correspond to values reported in the literature. Moreover, two-dimensional mappings are created that exhibit physiological meaningful relationships. Finally, the analysis of waveform data obtained via deconvolution shows plausible pulse transit behavior.

Keywords
Cardiorespiratory Movement, Motion Capture, Deconvolution, Biosignalprocessing, Unobtrusive Sensing

1. Introduction

Ambient and unobtrusive cardiorespiratory sensing techniques form an increasing sub-field within biomedical engineering \cite{1}. Sensor principles range from camera-based methods \cite{2} over ultrasound \cite{3}, radar \cite{4} and laser \cite{5} to force sensors \cite{2} and high-frequency oscillator circuits \cite{6}. For a comprehensive overview, the interested reader is referred to \cite{1}. While the sensors span a wide range of devices and physical principles, many methods that allow for unobtrusive monitoring of heart and lung are ultimately based on the analysis of thoracic movement. Most of the time, unobtrusive sensing modalities are evaluated in terms of their ability to detect respiratory rate, respiratory patterns, heart rate or beat-to-beat intervals. Thus, they are commonly compared to a medical gold standard, such as the electrocardiogram (ECG) or an air flow sensor. However, spatially resolved quantification of the actual thoracic motion is seldom performed. For this, specialized measurement equipment is necessary. Moreover, if cardiac induced motion is to be quantified, sub-millimeter accuracy is required. At the same time, spatially resolved information could help to optimize regions of interest for existing and future sensing modalities.

Thus, the aim of this proof-of-concept study is to develop a method for the spatially resolved analysis and mapping of cardiorespiratory induced thorax movement. For this, healthy volunteers sitting in an armchair are monitored with a high-performance motion capture (MoCap) system and an ECG. To extract and quantify the spatial impulse responses of cardiac and respiratory activity, deconvolution \cite{7} is used.

2. Materials and Methods

A Schematic of the overall system setup is given in Fig. \ref{1}. Three of the seven cameras used for MoCap which are placed around the subject in a semicircle are visualized.
2.1. Hardware

For motion capture, the “Oqus” system from Qualisys AB, Göteborg, Sweden configured with seven “Opus 500+” infrared (IR) tracking cameras and ten passive reflective markers was used. Each camera has a resolution of 4 megapixels at \( f_{s,\text{max}} = 180 \text{ Hz} \) and is equipped with a C-mount lens with a focal length of 13 mm. The aperture was set to \( f/4.0 \) and manual focusing was performed. Illumination was provided by rings of IR LEDs integrated into each camera unit. Marker positions were tracked at \( f_{s,\text{M}} = 100 \text{ Hz} \). For ECG acquisition, the “MP30” patient monitor, manufactured by Philips, Amsterdam, The Netherlands was used as analog front end. Digitalization was performed at \( f_{s,\text{A}} = 800 \text{ Hz} \) with a DAQ system which was synchronized with the cameras.

2.2. Trial Setup

Three healthy volunteers participated in the trial which was conducted as self-experimentation. A schematic of the marker positions is given in Fig. 2 A), which are further described in Tab. 2.2. Fig. 2 B) shows a photograph of the marker positions for one subject and in Fig. 2 C), the coordinate system is given, \( x \) being the right/left axis. Since the subjects are sitting in a chair with approximately 20° recline, \( y \) and \( z \) only approximate the dorsoventral and the craniocaudal axis, respectively.

![Marker positions schematic](image)

**Fig. 2.** A) schematic of marker positions, B) photography of actual marker positions, C) coordinate system.

<table>
<thead>
<tr>
<th>#</th>
<th>Position x</th>
<th>Position z</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Central axis</td>
<td>Center of forehead</td>
</tr>
<tr>
<td>2</td>
<td>Right nipple</td>
<td>1 cm above right nipple</td>
</tr>
<tr>
<td>3</td>
<td>Central axis</td>
<td>Sternum, superior part</td>
</tr>
<tr>
<td>4</td>
<td>Left nipple</td>
<td>1 cm above left nipple</td>
</tr>
<tr>
<td>5</td>
<td>Central axis</td>
<td>Sternum, inferior part</td>
</tr>
<tr>
<td>6</td>
<td>Right nipple</td>
<td>1 cm below costal margin</td>
</tr>
<tr>
<td>7</td>
<td>Central axis</td>
<td>As 6 and 8</td>
</tr>
<tr>
<td>8</td>
<td>Left nipple</td>
<td>1 cm below costal margin</td>
</tr>
<tr>
<td>9</td>
<td>Centered between 6 and 7</td>
<td>Navel</td>
</tr>
<tr>
<td>10</td>
<td>Centered between 7 and 8</td>
<td>Navel</td>
</tr>
</tbody>
</table>

Tab. 1. Position of reflective markers for motion capture.

2.3. Data Analysis

The proposed model is shown in Fig. 3. The motion of each marker \( i \) is described as \( y_i \) and is influenced by a cardiac and a respiratory component. For each marker, these components are generated by filtering a virtual train of impulses originating from the heart and the lung with marker-specific transfer functions \( a_{\text{card},i} \) and \( a_{\text{resp},i} \), respectively. If \( y_i, a_{\text{card},i} \) and \( a_{\text{resp},i} \) are known, the filter coefficients can be estimated via deconvolution [7].

![Deconvolution diagram](image)

**Fig. 3.** Proposed source-filter structure of thoracic movement influenced by a superposition of cardiac and respiratory component. For each marker \( i \) and axis \( x, y, z \), individual filters \( a \) exist.

In the proposed approach deconvolution is performed separately for the cardiac and the respiratory component. For either component, the convolution is described by

\[
y_i[n] = \sum_{\tau=0}^{Q} a_i[\tau] s[n - \tau] + z[n], \tag{1}
\]

where \( n \) is the discrete time, \( Q \) the filter order and \( z \) is additive noise. The subscripts ‘card’ and ‘resp’ are omitted for reasons of brevity. In the Fourier domain, this can be expressed via

\[
y_i[k] = \sum_{\tau=0}^{Q} a_i[\tau] \tilde{s}[k] e^{-j2\pi k \tau / N} + \tilde{z}[k]. \tag{2}
\]

Here \( \tilde{s}[k], \tilde{z}[k] \) and \( \tilde{z}[k] \) are the Fourier transforms of their time-domain equivalents. The discrete frequency is marked by \( k \) and \( N \) is the number of samples. The filter coefficients are not transformed but the delay is expressed explicitly by the term \( e^{-j2\pi k \tau / (N-1)} \). This can be expressed in matrix notation as

\[
y_i[k] = a_i \cdot \mathbf{s}[k] + \tilde{z}[k], \tag{3}
\]

with the Fourier-domain delay-vector

\[
\mathbf{s}[k] = \left[ e^{-j2\pi k/N}, \ldots, e^{-j2\pi kQ/N} \right]^T \tag{4}
\]

and the vector of filter coefficients

\[
a_i = [a_i[0], a_i[1], \ldots, a_i[Q]]. \tag{5}
\]
Let $[·]^T$ be the transpose, $[·]^H$ the Hermitian transpose and $[·]^*$ the conjugation operator. If the source signal is known, the optimal filter coefficients in terms of a minimal quadratic error can be determined with

$$a_i,est = \left[ y^* \cdot ES^T + y \cdot ES^H \right]^{-1} \left[ ES^* \cdot ES^T + ES^* \cdot ES^H \right],$$

with the matrix

$$ES = [e[0] \cdot s[0], e[1] \cdot s[1], \ldots, e[N-1] \cdot s[N-1]]$$

and the vector

$$y_i = [y_i[0], y_i[1], \ldots, y_i[N-1]].$$

For a more detailed derivation, the interested reader is referred to [8], where a modified version of the algorithm is applied to multichannel blind deconvolution. In this scenario, filter and source are unknown and inferred from multichannel observations.

Note that the calculations are carried out separately for all $i$ markers, for the respiratory component and for the cardiac component. Moreover, a separate filter is estimated for the each dimension $x$, $y$, and $z$. To obtain the cardiac related motion $y_{i, \text{card}}$, the marker position is filtered with a second-order Butterworth bandpass with 0.8 to 30 Hz passband. The respiratory component $y_{i, \text{resp}}$ is obtained via filtering with a passband of 0.01 to 0.3 Hz. The cardiac impulse signal $s_{\text{card}}$ is obtained from R-peaks of the ECG, while $s_{\text{resp}}$ is obtained via peak-detection on the geometric mean of $y$ and $z$ component of the central marker #5. To quantify the cardiac and respiratory induced motion, the range of $a_i,est$, i.e. the maximum minus the minimum of the respective impulse response, is calculated. For visualization, the range is color-coded and interpolated, the mapping is shown in Fig. 4.

3. Results and Discussion

In Fig. 6, the color-coded ranges are visualized. Several observations can be made. First, neither cardiac nor respiratory activity create a significant $x$ (i.e. left-right) motion in any subject, which is to be expected. Next, the strongest respiratory motion is observed in the $y$ (dorsoventral) direction and occurs in the belly area, whereas the strongest $z$ (cranio-caudal) component is measured in the upper part of the thorax. This is consistent with normal physiological breathing in rest, where the ribcage is lifted only slightly and the strong downward motion of the diaphragm displaces organs which extend the belly. In terms of amplitude, the maximum respiratory induced motion is in the range of 5 to 7 mm, while the maximum cardiac induced motion ranges from 0.25 to 0.3 mm, which is consistent with values reported in the literature [9, 10]. In conclusion, more than an order of magnitude lies between the cardiac and the respiratory effect. Similar to the observations made with respect to respiration, the strongest $z$ component can be measured in the upper part of the thorax close to the heart, whereas the strongest $y$ movement of the thorax due to cardiac activity occurs in the belly region. At the same time, a relatively strong $y$-motion of approximately 0.25 mm can be observed on the foreheads of all subjects. Compared to the thoracic region, the influence of respiratory induced motion on the forehead is relatively low.

In Fig. 5, the impulse response of the $z$-component of marker 4 and 9 are shown for subject 1. On can see that the largest peak occurs at 110 ms in the timecourse of marker 4, whereas for marker 9, the largest peak is found at 310 ms. Thus, the marker closest to the heart exhibits a delay of 110 ms with respect to the R-peak, i.e. the electrical activity, whereas the pulse transit time between both markers is 200 ms.
Fig. 6. Mapping of respiratory (left) and cardiac (right) induced movement, see also Fig. 4. For each subject, an individual color code was used for respiratory and cardiac movement, which was constant for $x$, $y$, and $z$ component. Values are given in mm.
4. Conclusions and Outlook

In this paper, the use of motion capture and deconvolution to quantify cardiorespiratory thorax movement was demonstrated. Using a high-performance MoCap system and an ECG, movement amplitudes from three healthy subjects were obtained that are consistent with values reported in the literature. From these values, spatially resolved maps were created that exhibit physiological plausible distributions. Moreover, the phenomenon of pulse transit could be observed and quantified. In the future, a larger study with a statistical analysis needs to be performed. It is hoped that our findings can be used in the future for the optimization of regions of interest for unobtrusive sensing, for example by focusing on the head or belly region.

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References


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Christoph HOOG ANTINK was born in Lohne (Oldenburg), Germany in 1985 where he finished his Abitur in 2005 and then began his studies in Aachen. As a visiting student on a Fulbright Travel Grant he obtained a M.S. degree in mechanical engineering from the University at Buffalo, Buffalo, New York, USA in 2011. In 2012 he finished his diploma in electrical engineering at the RWTH Aachen University where he is currently working towards a Ph.D. degree in electrical engineering at the Philips Chair for Medical Information Technology. His research interests include medical sensor fusion and imaging technologies.

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