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Unobtrusive ECG monitoring in the NICU using a capacitive sensing array

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Abstract

The thin skin of preterm babies is easily damaged by adhesive electrodes, tapes, chest drains and needle-marks. The scars caused could be disfiguring or disabling to 10% of preterm newborns. Capacitive sensors present an attractive option for pervasively monitoring neonatal ECG, and can be embedded in a support system or even a garment worn by the neonate. This could improve comfort and reduce pain aiding better recovery as well as avoiding the scars caused by adhesive electrodes. In this work, we investigate the use of an array of capacitive sensors unobtrusively embedded in a mattress and used in a clinical environment for 15 preterm neonates. We also describe the analysis framework including the fusion of information from all sensors to provide a more accurate ECG signal. We propose a channel selection strategy as well as a method using physiological information to obtain a reliable ECG signal. When sensor coverage is well attained, results for both instantaneous heart rate and ECG signal shape analysis are very encouraging. The study also provides several insights on important factors affecting the results. These include the effect of textile type, number of layers, interferences (e.g. people walking by), motion severity and interventions. Incorporating this knowledge in the design of a capacitive sensing system would be crucial in ensuring that these sensors provide a reliable ECG signal when embedded in a neonatal support system.
Keywords: ECG, neonate, capacitive, channel selection, sensor

(Some figures may appear in colour only in the online journal)

1. Introduction

Although in term infants the skin is structurally similar to that of adults, it is incompletely developed in preterm neonates (Evans and Rutter 1991, Shwayder and Akland 2005). In a baby of 26 weeks gestation the epidermis is only 2–3 cell layers thick and the keratinized stratum corneum barely visible. It is not until 34 weeks gestation that the stratum corneum is well defined and the skin functionally competent. Although it can be argued that cosmetic skin damage during a neonate’s stay in the NICU is a consequence of several standard tests and procedures, the prevalence of scars in about 10% of infants can be disabling or disfiguring to the infant (Cartiledge 1991). Chest drains and needle-marks in addition to adhesive electrodes and tapes can contribute to skin damage in such a vulnerable patient population. Pain during hospital care could also have severe effects on long term developmental outcomes for this vulnerable population (Bhutta and Anand 2002).

Capacitive sensing offers the advantage of measuring electro-physiological signals without direct skin contact. It can be integrated in materials that can be worn by a person, or embedded in objects surrounding the body, such as a chair or a mattress. This is advantageous, in particular, when a lengthy measurement has to be conducted. In this technique, a capacitor is effectively formed in which the human skin acts as one of the capacitor plates and the electrode of the sensor acts as the other capacitor plate. Capacitive measurement techniques can potentially be integrated into a range of everyday objects: office chairs, bathtubs (Lim et al 2004), toilet seats (Kim et al 2004), cars (Leonhardt and Aleksandrowicz 2008) and beds (Ueno et al 2007).

Capacitive sensing has shown promise in many applications where an ECG signal is required (Ueno et al 2007, Yama et al 2007). Recently, work by Weil et al (2012) showed that capacitive sensors can be used to identify anterior and inferior ST elevation myocardial infarction in the ECG signal (validated with contact electrodes). Capacitive sensors, however, were applied in an array directly above the patients’ chests without any layers in between. This set-up, also used in Oehler et al (2008), is not quite unobtrusive despite embedding the sensors in a portable system. Work by Eilebrecht et al (2012) investigated ECG feature extraction from a capacitive ECG system embedded in a pillow placed between a subject’s back and a chair. Although their results were promising, their work cannot be directly translated to the NICU environment. The main reason is that the effects of motion, subject positioning and the number of layers between subject and sensors were not addressed. These factors are also not considered in Hoshino et al (2006), who embedded 2 capacitive sensors and a reference in neonatal underwear, assuming that neonates are always lying in a supine position in the incubator. In fact, neonates can be placed in several positions: supine, prone or side positions. They can move a lot, especially when agitated or unwell. They also undergo several procedures per day such as diaper changes, feeding and tests (ultrasound for example). All these factors can affect the quality of the signal obtained from capacitive sensors, and should be addressed in a real-life scenario aiming to provide ECG monitoring in the NICU.

This work proposes the use of an array of capacitive sensors unobtrusively embedded in the mattress of the neonate. The use of an array allows the development of an analysis framework focusing on channel selection for sensor fusion from different capacitive sensors.
This is important during neonatal motion and positioning as these factors can cause incomplete coverage of the sensor array leading to signal loss. To investigate coupling further, we compare the use of coupling strength, channel correlation and spatial distribution of channels for robust channel selection. This is followed by using neonatal position combined with an adaptive Kalman filter to derive an ECG signal. We analyse instantaneous heart rate coverage then compare ECG features, such as the beat-to-beat distance (RR interval), between the derived capacitive signal and the reference ECG from the adhesive electrodes.

2. Methods

2.1. Physical set-up and hardware description

In this work, eight capacitive sensors are embedded in a mattress that is used in the incubator. The area of sensors has been chosen to allow sufficient capacitive coupling to the neonate’s skin. The distance between the sensors ensures that at least two sensors overlap with the neonate’s body, which is required to be able to measure an ECG signal. Since our data acquisition platform supports eight sensors only, the flower-shaped sensor configuration appeared to be the most effective and efficient choice. The sensors are located in the middle of the mattress and are surrounded by a reference electrode made of conductive textile, as shown in figure 1. The mattress is covered by a polyurethane (PU) cover (of 1 mm thickness), making it impermeable for fluids (e.g. urine) and easy to clean. All sensors and the reference electrode inside the mattress can be connected to the electronics box using a connector.

In order to reduce the impact of motion on the sensor signal we implemented a so-called neutralization technique (Veen et al 2011) that aims to eliminate the (parasitic) input capacitance of each sensor amplifier. In an ideal case this technique makes the transfer function of all sensor channels equal to 1. Because of the channel balancing effect this technique also contributes to the rejection of common-mode (CM) interferences (e.g. 50/60 Hz mains interference), e.g. when equally subtracted. In order to observe the coupling strength of different channels in real-time, we injected a low current high frequency (1 kHz) signal. A similar approach was also used in Wartzek et al (2012) to look at sensor coupling leading to the development of a hardware solution for sensor selection. The signal injection used in Wartzek et al (2012) was via the common reference electrode (more specifically via the...
driven-right-leg electrode). The same implementation would not work in our case, since the neutralization technique would make the injected signal insensitive to variations in coupling strength. This is the main reason behind implementing the signal injection technique at the sensor side for individual sensors in this work. It is worth noting that this signal injection technique was not specifically used for motion artefact reduction.

In the electronics box the sensor signals are first processed by the analogue front-end board. This board provides all necessary analogue processing, i.e. filtering, amplification and reduction of interferences (via the reference electrode). Data from the analogue front-end board and control to the board are provided via a data acquisition platform that performs analogue to digital and digital to analogue conversion. Moreover this platform provides the interface capabilities to a laptop via a galvanic separator. The galvanic separator is properly positioned in the signal chain to separate circuits supplied by medical supply to circuits not medically certified. A medically certified power supply provides energy (from the mains) to the electronic platform. The standard ECG signal, measured with gel electrodes, is logged simultaneously and is used as a reference for performance assessment of the capacitive ECG signal. In addition, to be able to interpret position and orientation of the neonate and disturbances in the data (e.g. due to neonate’s movements, medical interventions) a camera is present. All data is processed and stored on a laptop using LabVIEW and Matlab software.

2.2. Overall algorithm description

The algorithm is composed of two main parts, the first focusing on appropriate channel selection from the sensors and the second on fusing the data in a framework resulting in a signal similar to standard ECG signals. Figure 2 summarizes the main elements of the algorithm used in this work. These are adaptive channel selection, followed by filtering/down-sampling the selected channels, computing a vectorcardiogram (VCG) and projecting it to a predefined direction based on the infant position. This is followed by using a wavelet-based peak detection method to locate R-peaks (characteristic peak in the ECG), then Kalman filtering the ECG.
signal of each selected channel and recomputing the VCG using the Kalman filtered data. The final step projects the recomputed VCG on standard Einthoven leads. The following section presents the elements of this algorithm in more detail.

2.3. Adaptive channel selection

Neonates can be placed in different positions: prone, supine and sideways as well as positions in between. These positions, in addition to the status of the neonate and ambient environment, can affect neonatal motion. If the neonate is restless, or ill, several motion patterns can be observed such as moving the hands and legs. Thus, to continuously monitor the neonate with capacitive sensor arrays, a robust channel selection strategy is important to reconstruct an ECG signal from the most relevant sensors. The relative positions for these channels in the matrix are shown in figure 3(a). As shown in figure 3(b), the ECG signal is reflected well in some channels (1 and 2). However, some channels such as channel 7 in this case, fail to adequately
show the ECG signal. Including them in the analysis would lead to a wrong representation of the ECG. The following steps are used for channel selection:

- **Using coupling strength.** The amplitude of the injected 1 kHz tone is inversely proportional to the coupling between sensor and the body, so better coupling indicates lower overall amplitude at that frequency. The coupling strength, allowing the ranking of channels, is derived from the averaged amplitude of the band-passed signal at the 1 kHz frequency.

- **Rejecting bad channels.** Channels that show out of bound signals are taken out of the list of selected channels. This can be judged by using the ratio of the variance of amplitude of each channel, over the variance of the best channel (selected using coupling). The bad channels are normally the ones showing the highest overall motion, as well as the lowest coupling with the body (Veen et al. 2011).

- **Channel correlation.** Pearson’s correlation coefficient was used to assess the correlation between the best-coupled channel and all the others. This provides a means to judge how well ECG data is captured by these channels, assuming that the best coupled channel is the one that best captures ECG data.

- **Using spatial distribution.** Using a weighing matrix, we introduce a penalty for very close channels as they could be providing very similar information. This step can be used to introduce the geometry of the channels in the selection criteria. Weights can be adapted to array shape.

We noticed that in most cases, the first three steps were enough to give a ranking of the best channels. Penalizing channels for positioning (or spatial distribution) could actually lead to worse results for scenarios where only 2 or 3 channels are actually coupled to the body. This is true especially if the close channels are the ones producing the best signals, rather than the ones that are far-off. However, using spatial distribution as an extra feature improved the results when the channel coupling was good.

2.4. Fusion of information for ECG reconstruction

Although many methods have been investigated for ECG reconstruction from a number of channels such as blind source separation (De Lathauwer et al. 2000, Vaya et al. 2007) and template matching, we have chosen to build on the algorithm by Vullings et al. (2012). This algorithm utilizes a physiological model incorporating electrode position with respect to the subject. Despite similarities in the analysis framework between this work and that of Vullings et al. (2012), the application is completely different. Compared to foetal monitoring investigated in their work, this paper investigates non-contact capacitive sensors embedded in a subject’s support system which is quite different from using contact electrodes on the mother’s body to monitor a foetus. Next, we will present the steps we undertook in data processing after the channel selection stage.

2.4.1. Preprocessing. The data from the selected channels was down-sampled from 8000 to 250 Hz. A band-pass filter of 3–35 Hz was then used to suppress frequency components outside the (dominant) ECG band. This allows the removal of the 50/60 Hz CM interference. Note that the same filters were used for the reference ECG signals to ensure proper synchronization between the capacitive and reference signals. As the motion of people nearby can affect the signals acquired from capacitive sensors (as explained in Wimmer et al. 2007), we averaged the signals across the sensor array and subtracted this average from each channel to remove CM interferences.
2.4.2. VCG Computation. Given the electrode position with respect to the subject’s heart, the VCG for several overlaid heartbeats can be approximated (Vullings et al 2010). The VCG (shown in figure 4(a)) is a weighted projection of the ECG signals from the selected channels on 2 axes in this case. Each weight for the projection is the distance of the electrode to the centre of gravity of the electrode array.

2.4.3. VCG projection and R-peak detection. The VCG is projected on the spatial direction that enhances R-peaks, that is the one similar to lead II, in order to allow optimal R-peak detection. The projection axis is selected here as a fixed direction given the neonate’s position. The neonate’s position can be entered manually (as we did here) or automatically detected (Brauers and Meftah 2009).

The use of wavelets for the detection of R-peaks on the projected signal is based on the work of Rooijakkers et al (2012), who use the discrete-time continuous wavelet transform (DT-CWT), as a means to locally band-pass filter the signal and detect R-peak positions. The technique was validated in Rooijakkers et al (2012) for standard ECG monitoring, where a Mexican hat wavelet proved to be an adequate choice for R-peak detection. The DT-CWT of a signal \( x[n] \) with respect to a wavelet function \( \psi(n) \) is:

\[
\text{CWT}_s[\tau] = \frac{1}{\sqrt{s}} \sum_{n=-\infty}^{\infty} x[n].\psi \left[ \frac{n - \tau}{s} \right]
\]  

(1)

where \( s \) is a scaling factor and \( \tau \) is the translation parameter in time. The variation of \( s \) allows the control of the peak frequency of the wavelet’s band-pass filtering effect. The wavelet transformation of the ECG signal is followed by segment selection, threshold determination, SNR estimation and finally peak detection (Rooijakkers et al 2012). The R-peak positions allow the computation of the RR interval time as well as the instantaneous heart rate. An example of the projected signal and the detected peaks is given in figure 4(b).

2.4.4. Kalman filtering, VCG re-computation and projection on the Einthoven leads. To enhance the quality of each selected ECG signal, consecutive QRS complexes can be averaged triggered by the heartbeat. However, this averaging constitutes a trade-off between improvement of the SNR and loss of clinically relevant physiological signal dynamics. In this work, we have used a Bayesian framework to improve the quality of ECG signals (Vullings et al 2011). A sequential averaging filter adaptively varies the number of complexes included in the averaging based on the characteristics of the ECG signal. The filter has the form of an adaptive Kalman filter. The adaptive estimation of the process and measurement noise covariances is performed by maximizing the Bayesian evidence function of the sequential ECG estimation and by exploiting the spatial correlation between several simultaneously recorded ECG signals. The noise covariance estimates thus obtained render the filter capable of ascribing more weight to newly arriving data when this data contains morphological variability, and of reducing this weight in cases of no morphological variability (Vullings et al 2011). The adaptive Kalman filter stage is applied to each selected ECG signal to obtain clearer signals of neonatal ECG.

The VCG is then re-calculated from the Kalman-filtered signals. It is then projected on the standard Einthoven leads that are used in ECG analysis (Vullings et al 2011), enabling clinicians to observe a similar signal to adhesive electrodes. A projection of the VCG on Lead II (Einthoven) lead, as an example, is shown in figure 4(c) compared to the reference signal in 4(d).
Figure 4. The VCG is shown in (a) and its projection with the peaks detected in (b). Figure (c) shows the resulting capacitive ECG after Kalman filtering/projection on standard Einthoven leads and (d) the corresponding reference ECG. The gain settings are different for the capacitive and reference ECG signals which explains the difference in amplitude between them.
3. Evaluation

3.1. Experimental setup

The study was conducted at the NICU (neonatal intensive care unit) and NMCU (neonatal medium care unit) of the Maxima Medical Centre in Veldhoven the Netherlands, after being approved by the hospital’s medical ethics committee. Fifteen neonates (from both the NICU and NMCU) were included in this study after their parents consented to having them participate. Figure 5(a) shows the distribution of these neonates among four weight classes between the NICU and NMCU. Low weight neonates were more difficult to recruit as they are normally born very early and are quite vulnerable. Around 75 h of data were collected in total. As we could not control the number of layers between each neonate and the capacitive array, these layers varied from case to case. For example the caregivers and parents decided whether the neonate should wear clothes or not. Figure 5(b) illustrates the different layers. As shown, the first layer which is always present is the polyurethane (PU) cover of the mattress. In most cases a cotton bed sheet is put on the mattress. Furthermore, the neonate with or without clothes (1 or 2 layers) is positioned in a cotton support system. Table 1 shows the positions...
Table 1. This table shows the positions, alignment with sensors and layers between neonate and sensors throughout the recording for each neonate. Positions are: C(chest), B(back), R(right side), L(left side), M(mixed). Layers between neonate and sensors are: PU(polyurethane cover) and CL(cotton layer).

<table>
<thead>
<tr>
<th>Number</th>
<th>Positions</th>
<th>Alignment with sensors</th>
<th>Layers between neonate and sensors</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>C</td>
<td>Good</td>
<td>PU+2CL</td>
</tr>
<tr>
<td>2</td>
<td>CBRLM</td>
<td>Good</td>
<td>PU+2CL</td>
</tr>
<tr>
<td>3</td>
<td>CRL</td>
<td>Good</td>
<td>PU+2CL</td>
</tr>
<tr>
<td>4</td>
<td>C</td>
<td>Good</td>
<td>PU+2CL</td>
</tr>
<tr>
<td>5</td>
<td>R</td>
<td>Bad</td>
<td>PU+2CL</td>
</tr>
<tr>
<td>6</td>
<td>RL</td>
<td>Good</td>
<td>PU+4CL</td>
</tr>
<tr>
<td>7</td>
<td>CR</td>
<td>Bad</td>
<td>PU+2CL</td>
</tr>
<tr>
<td>8</td>
<td>C</td>
<td>Good</td>
<td>PU+2CL</td>
</tr>
<tr>
<td>9</td>
<td>RL</td>
<td>Good</td>
<td>PU+2CL</td>
</tr>
<tr>
<td>10</td>
<td>BM</td>
<td>Good</td>
<td>PU+2CL</td>
</tr>
<tr>
<td>11</td>
<td>C</td>
<td>Good</td>
<td>PU+3CL</td>
</tr>
<tr>
<td>12</td>
<td>CBRLM</td>
<td>Bad</td>
<td>PU+2CL</td>
</tr>
<tr>
<td>13</td>
<td>CL</td>
<td>Bad</td>
<td>PU+3CL</td>
</tr>
<tr>
<td>14</td>
<td>CB</td>
<td>Good</td>
<td>PU+3CL</td>
</tr>
<tr>
<td>15</td>
<td>BM</td>
<td>Bad</td>
<td>PU+3CL</td>
</tr>
</tbody>
</table>

for each neonate, the alignment with sensors as well as layers used between the neonate and sensors. In this table, PU+2CL, for example, indicates the use of a polyurethane cover and two cotton layers.

A camera was available for some of the neonates, so we used the video data offline to segment motion classes into the following categories (if present): no motion, low motion, high motion and interventions (such as changing diapers). We also added a sub-category of interventions, namely test interventions including ultrasounds and hearing tests. For neonates where camera data was not available, we used the amplitude of the 1 kHz reference tone on each of the capacitive sensors in order to deduce whether a sensor is coupled sufficiently to the body or not. In this way we estimated the motion severity as well as the proper positioning of the neonate on the sensors. By observing this data, we empirically chose two thresholds to classify three groups of motion: low, medium and high motion. The results section will present these groups as two categories, with and without camera as the motion classes are different for the two cases.

3.1.1. Statistical analysis. To analyse the heart rate data obtained for all neonates, we compare the R-peak detections performed on capacitive ECG versus reference ECG signals. A true positive is defined when the R-peak detection in the capacitive ECG matches the one in the reference ECG. A false positive is when an R-peak is detected in the capacitive ECG but is not present in the reference ECG. A false negative is when an R-peak is missed in the capacitive ECG. These values are used to calculate the sensitivity (SEN) and the positive predictive value (PPV).

Comparing the distance between two R-peaks (i.e. the RR-interval) in the capacitive ECG and reference ECG gives us an indication of the percentage of time during which the quality of the capacitive ECG is equivalent to that of the reference ECG. The time coverage (in %) is defined as the sum of all RR-intervals that match between the two signals divided by the total length of the signal. The time coverage is thus the percentage of time during which the instantaneous heart rate is reliable.
Table 2. Neonates with available camera data. This data was used by an observer to segment motion into several groups. The table shows the percentage of time when the instantaneous heart rate was accurately computed as well as the sensitivity and positive predictive value (SEN,PPV) of the R-peak detection for each type of motion.

<table>
<thead>
<tr>
<th>Neonate</th>
<th>Time coverage</th>
<th>All data total time (SEN,PPV)</th>
<th>No motion time (SEN,PPV)</th>
<th>Low motion time (SEN,PPV)</th>
<th>High motion time (SEN,PPV)</th>
<th>Interventions time (SEN,PPV)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baby 1</td>
<td>86%</td>
<td>312 min (87.2,99)</td>
<td>198 min (86.7,99.3)</td>
<td>14 min (89.98.8)</td>
<td>NA</td>
<td>92 min (74.2,97.4)</td>
</tr>
<tr>
<td>Baby 3</td>
<td>29%</td>
<td>310 min (46.1,92.2)</td>
<td>87 min (45.9,93.4)</td>
<td>135 min (53.9,94.9)</td>
<td>29 min (49.93.8)</td>
<td>25 min (32.7,87.3)</td>
</tr>
<tr>
<td>Baby 4</td>
<td>63%</td>
<td>170 min (71.3,96)</td>
<td>80 min (89.2,98.7)</td>
<td>245 min (70.8,96.5)</td>
<td>13 min (70.4,91.8)</td>
<td>12 min (54.4,96.2)</td>
</tr>
<tr>
<td>Baby 5</td>
<td>7%</td>
<td>439 min (23.8,1.7)</td>
<td>98 min (23.8,9.5)</td>
<td>144 min (22.6,86.6)</td>
<td>110 min (18.9,73.6)</td>
<td>86 min (29.3,75.2)</td>
</tr>
<tr>
<td>Baby 6</td>
<td>33%</td>
<td>218 min (43.9,90.9)</td>
<td>73 min (20.3,87.2)</td>
<td>99 min (47.9,92.3)</td>
<td>42 min (77.4,91.9)</td>
<td>3 min (16.5,68.2)</td>
</tr>
<tr>
<td>Baby 7</td>
<td>57%</td>
<td>326 min (65.6,98)</td>
<td>180 min (74.5,98.8)</td>
<td>58 min (67.4,97.9)</td>
<td>43 min (44.6,94.9)</td>
<td>46 min (49.3,96.1)</td>
</tr>
<tr>
<td>Baby 8</td>
<td>76%</td>
<td>374 min (82.4,99.1)</td>
<td>225 min (88.2,99.4)</td>
<td>103 min (78.7,99.1)</td>
<td>4 min (54.4,97.2)</td>
<td>42 min (63.6,96.1)</td>
</tr>
</tbody>
</table>

To analyse the shape of the ECG signal, we calculated temporal features related to peaks on the ECG curve, in a similar manner to Eilebrecht et al (2012). For this purpose, we detected the PQRST peaks using the method by Martinez et al (2004), which consists of a wavelet-based ECG delineation enabling accurate detection. We then analysed the agreement between the capacitive and reference ECG features (including RR distances) with Bland–Altman plots, standard error, 95% confidence intervals of the difference between the two means with upper and lower limits of agreement (UL and LL respectively, equal to the mean difference ±1.96 multiplied by the standard deviation of the difference). Data was analysed using specific code written in Matlab (Mathworks, Inc., Cambridge, UK).

4. Results

In this section, we will start by presenting the results in terms of instantaneous heart rate quality for all neonates recruited, with a focus on a few illustrative examples on the importance of layers, positioning and motion. We will then extend the analysis on one neonate where we had good signal quality to illustrate the potential of this technique in deriving ECG signal features when electrode coupling conditions are met.

4.1. Quality of the R-peak detection and instantaneous heart rate computation

As we explained in section 3.1, we will divide our neonates into 2 groups: neonates with camera data, whose heart-rate coverage results are given in table 2, and those without camera data whose results are in table 3. Both tables show the results for the comparison between the capacitive and reference ECG. Since many of the neonates did not have total body coverage over all sensors, the best overall results in this case were obtained when the best two selected channels were used, using the framework in section 2.3. Thus, the difference between these two channels was calculated and used for R-peak detection. This also enabled the subtraction of CM artefacts affecting the channels, such as that of people walking by. The tables show the
Table 3. Neonates where camera data was not available. The amplitude of the injected signal was used to segment the motion categories. The table shows the percentage of time when the instantaneous heart rate was accurately computed as well as the sensitivity and positive predictive value (SEN, PPV) of the R-peak detection for each type of motion. Baby 12’s data is divided into two parts as it includes recordings in the NICU (157 min) and NMCU (213 min).

<table>
<thead>
<tr>
<th>Neonate</th>
<th>Time coverage</th>
<th>All data total time (SEN, PPV)</th>
<th>No motion time (SEN, PPV)</th>
<th>Low motion time (SEN, PPV)</th>
<th>High motion time (SEN, PPV)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baby 2</td>
<td>70%</td>
<td>148 min (80.3, 98.4)</td>
<td>52 min (95.3, 99.8)</td>
<td>30 min (88.7, 99.7)</td>
<td>66 min (65.1, 96.1)</td>
</tr>
<tr>
<td>Baby 9</td>
<td>21%</td>
<td>225 min (38.7, 90.3)</td>
<td>11 min (51.6, 96.7)</td>
<td>26 min (42.9, 95.6)</td>
<td>185 min (37.6, 89.3)</td>
</tr>
<tr>
<td>Baby 10</td>
<td>38%</td>
<td>280 min (55.9, 95)</td>
<td>1 min (56.3, 80.3)</td>
<td>1 min (72, 100)</td>
<td>280 min (55.8, 950)</td>
</tr>
<tr>
<td>Baby 11</td>
<td>50%</td>
<td>107 min (64.4, 93.4)</td>
<td>13 min (82.3, 96.5)</td>
<td>15 min (78.3, 95.9)</td>
<td>79 min (58.9, 92.2)</td>
</tr>
<tr>
<td>Baby 12</td>
<td>68%</td>
<td>157 min (75.8, 96.1)</td>
<td>29 min (99.9, 99)</td>
<td>18 min (96.6, 99.7)</td>
<td>110 min (66.4, 94.4)</td>
</tr>
<tr>
<td>NICU stage</td>
<td>62%</td>
<td>213 min (74.9, 94.2)</td>
<td>27 min (95.3, 99)</td>
<td>31 min (94.4, 99.2)</td>
<td>155 min (67, 91.5)</td>
</tr>
<tr>
<td>Baby 13</td>
<td>40%</td>
<td>287 min (58.1, 93.6)</td>
<td>10 min (69.4, 96.7)</td>
<td>25 min (72.9, 98)</td>
<td>252 min (56.2, 92.9)</td>
</tr>
<tr>
<td>Medium care</td>
<td>72%</td>
<td>188 min (80.4, 97.8)</td>
<td>5 min (96.5, 99.7)</td>
<td>18 min (93.3, 99.8)</td>
<td>165 min (78.4, 97.5)</td>
</tr>
<tr>
<td>Baby 14</td>
<td>20%</td>
<td>342 min (36.3, 93.8)</td>
<td>37 min (52.2, 99.5)</td>
<td>33 min (48.8, 98.8)</td>
<td>271 min (32.7, 92.1)</td>
</tr>
</tbody>
</table>

Both tables 2 and 3 show that the R-peak detection and heart rate quality are greatly affected by experimental conditions. Neonates who were lying on their chest (baby 1 and 8) obtained better time coverage results, as well as SEN and PPV as opposed to neonates who moved between several positions. Neonates with optimal recording conditions, including good sensor alignment and a low number of layers are given in bold in tables 2 and 3. Note how the performance dropped during heavy motion and intervention periods as in many cases the neonate lost good contact with the sensor array during these periods (bad alignment). As table 1 shows, some neonates were not even lying above the sensors (marked as bad alignment with sensors), which meant bad results overall. An example is baby 5, who in addition to bad alignment had a high number of layers between the body and sensors, leading to extremely low coverage. Table 3 again shows how levels of motion affect the results. Baby 2, for example, shows a large SEN drop from 95.3% during no motion periods, to 65.1% during motion, which could also include interventions (as we could not validate that due to absence of camera data in this case).

4.2. Effect of material layers and positioning

To illustrate the effect of both textile layers and positioning on the accuracy of our results, we will focus on one of the neonates recruited for this study (baby 9). The data set was composed
Figure 6. This figure shows the SEN and PPV values for one of the neonates (baby 9). The first three recordings show low values as there were four layers of cloth between the baby and sensor array. In addition to that, the baby was lying on its side. The last two recordings show a much improved performance as one of the layers was taken out and the baby placed on its chest.

Table 4. Comparison of several channel selection strategies.

<table>
<thead>
<tr>
<th>Strategy</th>
<th>Time coverage</th>
<th>All data total time (SEN,PPV)</th>
<th>No motion time (SEN,PPV)</th>
<th>Low motion time (SEN,PPV)</th>
<th>High motion time (SEN,PPV)</th>
<th>Interventions time (SEN,PPV)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>86%</td>
<td>(85.99)</td>
<td>(95.8,99.7)</td>
<td>(90.1,99)</td>
<td>N/A</td>
<td>(68.6,97.8)</td>
</tr>
<tr>
<td>B</td>
<td>86%</td>
<td>(87.2,99)</td>
<td>(86.7,99.3)</td>
<td>(89.9,8.8)</td>
<td>N/A</td>
<td>(74.2,97.4)</td>
</tr>
<tr>
<td>C</td>
<td>80%</td>
<td>(82.2,98.9)</td>
<td>(80.8,99.1)</td>
<td>(86.7,98.9)</td>
<td>N/A</td>
<td>(76.9,79)</td>
</tr>
<tr>
<td>D</td>
<td>82%</td>
<td>(84.98.9)</td>
<td>(85.2,99.3)</td>
<td>(88.8,98.8)</td>
<td>N/A</td>
<td>(73.4,97.5)</td>
</tr>
<tr>
<td>E</td>
<td>58%</td>
<td>(68.8,97.8)</td>
<td>(66.7,97.6)</td>
<td>(58.96.4)</td>
<td>N/A</td>
<td>(61.8,97.2)</td>
</tr>
</tbody>
</table>

of five recordings of 225 min in total. Figure 6 shows the SEN and PPV values for each of these recordings. In the first three recordings, the neonate was lying on its side alternating between right and left. For these first recordings, there were four layers of cloth between the neonate and the sensor array. In the last two recordings, one of the cotton layers was removed and the neonate placed on its chest. This increased the SEN by more than 70% and the PPV by more than 23% indicating a much better match between the capacitive ECG and the reference ECG.

4.3. Comparison of channel selection strategies

In this section, we will focus on a dataset where optimal time coverage was mostly attained, namely that of baby 1. This dataset had low levels of motion overall, despite periods of intervention (changing diaper) and a hearing test (test intervention). Table 4 shows a comparison of several channel selection strategies using a moving window of 2 s. Adaptive channel selection throughout the dataset for every moving window enabled a selection of the preferred channels every 2 s. The channel selection strategies are as follows:
(A) Using the best two channels that match with the reference ECG: in this case, we used correlation with the reference ECG to select the top two correlated channels. We then subtracted these channels and used the resulting signal for peak detection. This is therefore a channel selection that requires the reference signal, but could act as a good guide for channel selection if a reference signal is present.

(B) Using the top two channels in the channel selection scheme described previously (section 2.3), then subtracting them and performing peak detection. This is an automatic method but only aims at obtaining the top two channels to look at peak positions.

(C) Using the top three channels in the automatic channel selection scheme combined with a proximity matrix to weigh channels according to location.

(D) Using the top three channels in the automatic channel scheme without using a proximity matrix.

(E) Using all eight channels without performing any channel selection.

In table 4, B–E present automatic methods i.e. not requiring reference data as a prerequisite for channel selection. The table shows that the worst results in terms of time coverage and R-peak detection SEN were obtained when no channel selection was used (E). This is probably due to including channels with sub-optimal coverage as the neonate was moving. The best coverage results are obtained for the automatic use of the top two channels selected by the selection framework (B). The results (for the total time) are even better than matching the channels with the reference signal (A), which illustrates the importance of an automatic channel selection strategy in obtaining an accurate ECG. Using the proximity matrix in this case (C) did not improve the results except for the intervention period, where the results are better than using the channel selection framework (D) without the proximity information. Compared to using two channels (B), the use of three channels (without proximity-D) showed slightly worse results. The reason for this could be that channels are not perfectly balanced, so CM interferences, such as someone walking by are not actually reflected equally across channels. Subtracting the average from each channel and using a VCG constructed from these channels does not remove this interference, and ends up affecting the peak detection results. Choosing only the top two channels and subtracting them from each other might cancel this CM interference better than using more channels and thus lead to better results. If more than two channels are chosen, the CM signal is not being completely cancelled. This is mainly due to the fact that the channels are not perfectly balanced, and the effect of the CM is not equally distributed. In addition to that, obtaining good results while choosing a low number of channels has the advantage of not making the method too dependent on the neonate’s position over a large number of sensors.

4.4. ECG wave feature analysis

For the analysis of ECG quality, we analyse temporal features of the ECG signal and compare capacitive ECG with reference data. For that purpose, we use the (standard) PQRST points detected in the capacitive signal and compare the following distances: RR, PQ, QT and QRS distances between capacitive and reference signals. We also focus on the neonate with optimal recording conditions (neonate 1—also presented in the previous section) to further analyse the shape of the ECG signal obtained. We also use the method B in the previous section for channel selection as it provided the best results for this case.

Table 5 shows the mean difference obtained between RR PQ, QT and QRS intervals from both capacitive and reference ECG. The first column indicates the number of points used for analysis. The mean difference, standard deviation of the difference, upper and lower limits of agreements are also shown. For RR distances, the mean difference for no motion
Table 5. This table shows the results of comparing RR, QRS, PQ and QT distances obtained from capacitive versus reference electrodes per motion category. The number of intervals is given, so is the mean difference, the standard deviation (of the difference), the lower limit of agreement (LL) and upper limit (UL). Note that the categories of intervention and test intervention were merged in the previous section, but we wanted to observe the effect of each on ECG shape so kept them separate in this case.

<table>
<thead>
<tr>
<th>Activity</th>
<th>Number of points</th>
<th>Mean difference</th>
<th>Standard deviation</th>
<th>LL</th>
<th>UL</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>RR distances</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No motion</td>
<td>11135</td>
<td>−0.35 ms</td>
<td>7.94 ms</td>
<td>−16.21 ms</td>
<td>15.54 ms</td>
</tr>
<tr>
<td>Slight motion</td>
<td>587</td>
<td>−0.62 ms</td>
<td>8.9 ms</td>
<td>−18.34 ms</td>
<td>17.25 ms</td>
</tr>
<tr>
<td>Intervention</td>
<td>2236</td>
<td>−14.35 ms</td>
<td>68.65 ms</td>
<td>−151.64 ms</td>
<td>122.94 ms</td>
</tr>
<tr>
<td>Test intervention</td>
<td>1212</td>
<td>−6.71 ms</td>
<td>58.02 ms</td>
<td>−122.75 ms</td>
<td>109.33 ms</td>
</tr>
<tr>
<td><strong>QRS distances</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No motion</td>
<td>5344</td>
<td>−6.1 ms</td>
<td>6.71 ms</td>
<td>−19.1 ms</td>
<td>7.4 ms</td>
</tr>
<tr>
<td>Slight motion</td>
<td>99</td>
<td>−6.2 ms</td>
<td>2.95 ms</td>
<td>−12.11 ms</td>
<td>−0.3 ms</td>
</tr>
<tr>
<td>Intervention</td>
<td>128</td>
<td>−11.07 ms</td>
<td>13.46 ms</td>
<td>−37.99 ms</td>
<td>15.86 ms</td>
</tr>
<tr>
<td>Test intervention</td>
<td>585</td>
<td>−7.8 ms</td>
<td>10.7 ms</td>
<td>−29.27 ms</td>
<td>13.54 ms</td>
</tr>
<tr>
<td><strong>PQ distances</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No motion</td>
<td>3629</td>
<td>19.78 ms</td>
<td>11.24 ms</td>
<td>−2.71 ms</td>
<td>42.26 ms</td>
</tr>
<tr>
<td>Slight motion</td>
<td>132</td>
<td>24.21 ms</td>
<td>7.68 ms</td>
<td>8.85 ms</td>
<td>39.58 ms</td>
</tr>
<tr>
<td>Intervention</td>
<td>377</td>
<td>13.45 ms</td>
<td>16.49 ms</td>
<td>−19.52 ms</td>
<td>46.42 ms</td>
</tr>
<tr>
<td>Test intervention</td>
<td>528</td>
<td>23.14 ms</td>
<td>8.47 ms</td>
<td>6.23 ms</td>
<td>40.1 ms</td>
</tr>
<tr>
<td><strong>QT distances</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No motion</td>
<td>4686</td>
<td>−33.56 ms</td>
<td>30.65 ms</td>
<td>−94.86 ms</td>
<td>27.74 ms</td>
</tr>
<tr>
<td>Slight motion</td>
<td>217</td>
<td>−7.54 ms</td>
<td>30.65 ms</td>
<td>−68.84 ms</td>
<td>53.74 ms</td>
</tr>
<tr>
<td>Intervention</td>
<td>848</td>
<td>−9.9 ms</td>
<td>30.73 ms</td>
<td>−71.42 ms</td>
<td>51.47 ms</td>
</tr>
<tr>
<td>Test intervention</td>
<td>555</td>
<td>−1.2 ms</td>
<td>37.02 ms</td>
<td>−75.32 ms</td>
<td>72.76 ms</td>
</tr>
</tbody>
</table>

and slight motion shows excellent correspondence. In a similar study, Eilebrecht et al (2012) asked subjects to sit on a chair containing an array of capacitive sensors. They obtained a mean deviation of RR-interval differences of 50 ms, and compared averaged values over 5 s intervals. Our values of very low mean difference, especially for no motion and slight motion, show an improvement of RR values compared to their method.

The number of points used for analysis of QRS, PQ and QT distances is smaller than that of RR-distances, as intervals where any of the QRS points were missing were not considered for analysis. We observed almost a fixed value of 6 ms for mean difference between the QRS values obtained (capacitive and reference QRS values). This could be explained by the difference of electrode positions in the two cases. In the contact electrode case, the heart versus electrode position is different from that of the capacitive case where the sensors are in the mattress. Among the parameters analysed, the QT values seemed to be the ones with the largest standard deviation as the T-wave was particularly difficult to detect in the capacitive ECG signal.

5. Discussion and conclusions

This work showed an alternative method of ECG extraction for neonates which does not require adhesive gel electrodes. Although this presents an advantage for neonatal monitoring, using capacitive techniques has a set of challenges. In this section we will present some of the main observations derived from the results in the previous section. These observations can be used as guidelines for the design of a novel capacitive framework that can overcome many of the currently existing limitations.
The quality of the instantaneous heart rate was very good when proper electrode coupling conditions were attained. An example is baby 1 who was mostly in the chest position, with a low number of layers between neonate and sensor array. By developing an adaptive algorithm for channel selection, we were able to obtain good time coverage despite motion and intervention periods. The automatic channel selection method provided even better results, in terms of time coverage, than matching the capacitive sensors individually with the reference channel. Results were worse for babies with bad sensor alignment or with a large number of layers. This highlights the importance of designing a support system that enhances coupling. If sensor coupling is optimized, results of this method in terms of heart rate time coverage are very promising and can be used for local instantaneous heart rate analysis, supporting sepsis detection (Randall Moorman et al 2011) for example.

In this work, we selected temporal features to describe ECG signal shape which are standard in capacitive sensing analysis (Eilebrecht et al 2012). Due to the difference in electrode location and gain settings, it is difficult to analyse amplitude features and compare them directly to contact electrode ECG features. The heart is at a different distance to the sensors in both scenarios, which leads to a different signal shape. As in Eilebrecht et al (2012), we analysed RR, QRS, PQ and QT distances. The mean difference between capacitive and contact RR distance values is very small when sensor coupling is optimized (0.35 ms for still periods, 0.62 ms for slight motion), which provides an alternative method for measuring RR distances, leading to instantaneous heart rate. QRS distance analysis between capacitive sensors and contact electrodes also showed a low mean difference. However, the value was almost constant, most likely due to the difference in electrode positions between the two scenarios. The number of data points used for analysis for QT and PQ distances was lower than that used for RR interval and QRS analysis. The main reason being the difficulty of detecting the P and T waves in all signals. However, if an average distance is required (over a few seconds for example), the method could still be used to provide these distances.

From a signal processing perspective, we opted in this work for an approach that uses a physiological model incorporating electrode physiology with respect to the neonate’s body. It is worth comparing this technique to blind source separation techniques (De Lathauwer et al 2000, Vaya et al 2007). However, we felt that given the differences in body positions, the integration of this information in our model would provide a better understanding of the factors affecting our results. Although we used Kalman filtering as a smoothing step, we avoided the use of methods that completely ‘learn’ the signal shape, as we did not want important features, such as changes in QRS shape, to be missed.

To summarize our observations from the trial, we will highlight the factors that affected our results most, which can be thought of as limitations of this study; these are:

- **Effect of sensor alignment and position.** The neonate has to be lying over the sensors in order to accurately capture an ECG signal. We can see that the time coverage results are quite bad for neonates where the observer clearly noted bad positioning, namely neonates 5, 7, 12, 13 and 15. Misalignment could get even worse with motion leading to worse results during these periods as can be seen for all the above examples. It was also obvious that the chest (prone) position was the best for data coverage, followed by the back (supine). Side positions showed worse results mostly due to alignment with the sensors. Due to the size of the neonate, the side position hardly offers coverage of all sensors. In addition to that, the VCG projection assumes a 2D plane parallel to the sensors, which is difficult in the case of side-positions, as the plane of variation of the heart’s electrical vector is almost perpendicular to the plane containing the sensors. Figure 6 showed clearly that SEN and
specificity values for R-peak detection improved significantly after a layer of cloth was removed and the position of the neonate was changed.

- **Effect of motion and interventions.** The results show that motion has an important effect on heart rate quality and ECG signal reconstruction from capacitive data. Despite the detrimental effect of motion and interventions, we observed that if other conditions such as position and alignment are met, reasonable time coverage is attained. Examples are baby 1 and baby 8, that have SEN values of 74.2% and 63.6% respectively during interventions (generally very challenging periods). This is also observable for high motion periods for baby 4 (70%), baby 2 (65.1%) and baby 14 (78%).

- **Effect of external factors.** By external factors here we mean factors in the surrounding that are not due to child positioning, layering or alignment. Capacitive sensors can be responsive to movement in the environment caused by someone walking close by. To eliminate this effect, we used CM interference subtraction. This involved averaging the selected channel response and subtracting this average from each signal. This method can remove the effect of the person walking by if channels were perfectly balanced. However, in our case, the channels were not 100% balanced, so even if a CM was subtracted, we still had an effect that could manifest itself differently on different channels. This is the main reason why in our channel selection strategies, the best strategy was ‘B’ using two automatically selected channels and subtracting them from each other, which reduced the CM interference. Choosing more channels included this CM interference signal without proper cancellation, which led to worse results. Compared to the amplitude of a neonatal heart beat, the effect of a CM signal, due to external motion for example, can be quite large and hamper the detection of neonatal ECG. If the effect of the CM signal was equal over all channels, an adaptive channel selection strategy would be appropriate, where the top number of channels would adapt to different parts of the signal depending on positioning and motion. By ensuring better coupling between the neonate and sensors, the CM interference effect can be minimized. Using conductive textile in contact with any part of the body almost eliminates this effect, and can be thought of as an improvement in the design of the support system.

The above factors highlight the importance of physical conditions and environment on ECG signal quality. For optimal results, we would recommend the following:

- Embedding the sensors in a support system as close as possible to the neonate’s body. In this work, the sensors were embedded in a mattress under the neonate. However, an embedding in a closer support system could provide much better coupling. In addition to that, if embedded smartly, the sensors could provide a better 3D view of the heart activity, compared to a flat surface of the sensor plane embedded in the mattress. This would lead to a better reconstruction of the VCG and its projection to standard ECG leads.

- Designing the sensor matrix in the optimal way to attain good alignment of the sensors with the neonate’s body. Given how small these babies are, it is very important to have alignment over more than one point, especially when the neonate is lying on the side. For example, the shape of the sensor matrix itself can be changed to optimize alignment given the different body positions.

- Improving coupling between sensors and body. This can be attained by using a low number of layers between the child and sensor matrix. Alternatively, using conductive textile or changing material properties above the sensors could be alternatives to improve coupling.

In addition to enabling better mobility of the neonate in the incubator, capacitive sensors embedded in a (possibly wearable) support system would enable the monitoring of neonates even when they are out of the incubator. An example use case is that of Kangaroo care, where
a neonate is carried by an adult, allowing skin to skin contact. Kangaroo care has proven to offer many benefits for preterm infants (Cong et al 2009, 2012), reducing pain responses, improving cognitive development, sleep patterns, and normalizing growth. The availability of monitoring while the neonate is out of the incubator would encourage parents to do Kangaroo care for longer periods of time improving overall outcomes.

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References

Brauers A and Meftah M 2009 Sleep position detection Patent WO 2009074955 A1, 6
Leonhardt S and Aleksandrowicz A 2008 Non-contact ECG monitoring for automotive application ISSS-MDBS’08: 5th Int. Summer School and Symp. on Medical Devices and Biosensors pp 183–5
Oehler M, Ling V, Melborn K and Schilling M 2008 A multichannel portable ecg system with capacitive sensors Physiol. Meas. 29 783
Shwynder T and Akland T 2005 Neonatal skin barrier: structure, function, and disorders Dermatol. Ther. 18 87–103


