Bringing ICT into Newborn Monitoring: A Video-Based Approach

Davide Alinovi and Riccardo Raheli
Joint work with L. Cattani, G. Ferrari, G. M. Kouamou Ntonfo, F. Pisani

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University of Parma
Department of Engineering and Architecture (Information Engineering)
Department of Medicine and Surgery
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Outline

1. Introduction
2. Detection of seizures
3. Monitoring of respiration and its disorders
4. Simulators of neonatal disorders
5. Mobile application: smartCED
6. Conclusion
1 Introduction

2 Detection of seizures

3 Monitoring of respiration and its disorders

4 Simulators of neonatal disorders

5 Mobile application: smartCED

6 Conclusion
Neonatal diseases

Seizures

- Involuntary contractions of one or more muscle groups due to a paroxysmal neuronal discharge
- Age-dependent phenomena and symptoms of malfunctioning of the central nervous system
- Incidence: 2.6‰ for overall newborns, 11.1‰ for preterm neonates and 13.5‰ for underweight preterm neonates
- Four main categories: subtle, tonic, clonic and myoclonic

Respiration diseases

- Interruptions of the respiratory airflow
- Significant if longer than 20 s, or only 10 s if associated with other signs/symptoms (oxygen desaturation in the arterial blood, or hypoxemia)
- Different types: central, obstructive and mixed.
- Associated with life-threatening disorders or congenital diseases
- Incidence: 2.3% of hospitalized infants, and 0.5%–0.6% of all newborns
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Systems for patient monitoring

Seizures and nervous system diseases:
- Based on EEG, ECG and EMG systems

Respiration and apnea events:
- Measure the Respiratory Rate (RR)
- Based on chest/abdomen elastic belts or nasal flow meter

Both require prolonged monitoring and specialized medical staff

Challenge

Devise wire-free, non-invasive, low-cost monitoring systems

Sleep Apnea Guide (2016), The polysomnogram test [Online]. These devices are expensive and moderately invasive
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Contactless RR monitoring

- Microwave radar sensors
- Fiber optic sensors (e.g., integrated in “smart bed”)
- Networks of wireless sensors (e.g., WSNs around the patient)
- Wearable devices and smart-watches (e.g., smart sensors or clothing)

Possible solution

Video processing-based techniques for monitoring of respiration movements.

D. Dei et al., “Non-contact detection of breathing using a microwave sensor,” Sensors (MDPI), 2009.

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Video processing-based techniques for monitoring of respiration movements.


Video-processing based methods

- Video-processing algorithms to detect specific movements or to estimate the RR of the framed subject
- Monitoring the patient with one or more digital cameras
- Possibility to use the system in hospital or in domestic environments
- Video material obtained in the Neonatal Intensive Care Unit of the University Hospital of Parma
Video-processing based methods

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Early work

- N. B. Karayiannis et al.: **pioneering work** on the subject of seizure detection and analysis of newborns’ movements by video cameras
  - Based on motion tracking of the limbs (e.g., optical flow, block motion models, template matching)
  - Use of neural networks (NNs) for event detection and motion classification (different types of seizures)
  - Analysis of the motion strength and motor activity signals
  - Focused only on neonatal seizures
  - Methods involving optical flow, block matching and NNs may require algorithms for features extraction, learning and computationally inefficient systems

**Automated Detection of Videotaped Neonatal Seizures Based on Motion Tracking Methods**

*Nicolaos B. Karayiannis, * Yaohua Xiong, * James D. Frost, Jr., † Merril S. Wise, †‡
Richard A. Hrachovy, †§ and Eli M. Mizrahi †‡

Epilepsia (Wiley) 2006
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Quantifying Motion in Video Recordings of Neonatal Seizures by Regularized Optical Flow Methods

Nicolaos B. Karayiannis, Senior Member, IEEE, Bindu Varughese, Guozhi Tao, James D. Frost, Jr., Merrill S. Wise, and Eli M. Mizrahi
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Automated Extraction of Temporal Motor Activity Signals From Video Recordings of Neonatal Seizures Based on Adaptive Block Matching

Nicolaos B. Karayiannis*, Senior Member, IEEE, Abdul Sami, James D. Frost, Jr., Merrill S. Wise, and Eli M. Mizrahi
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Need for fast, straightforward and reliable algorithms for real-time analysis of newborns’ movements to promptly detect possible disorders
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Motion information extraction (1/2)

- Process video frames: four steps (gray-scale, DoF, binarization, erosion). This highlights the body parts affected by motion.
- Project the 2D signal into 1D by spatial averaging to significantly reduce complexity.
- Extract a signal representing the movement “pattern” of the involved body parts.
Seizures are characterized by specific movements of limbs or body parts.

**Clonic seizures**: periodic movements with a repetition time between $0.5–2.5$ s

*Example of clonic seizure in a newborn*
Seizures are characterized by specific movements of limbs or body parts.

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Extracted periodic movements correspond to an epileptic event in the EEG with comparable periodicity.
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**Clonic seizures**: periodic movements with a repetition time between 0.5–2.5 s.

Extracted periodic movements correspond to an epileptic event in the EEG with comparable periodicity.
Clonic seizures detection by periodicity analysis
Model of periodicity in the motion signal $\bar{L}[n]$: 

$$\bar{L}[n] = c + A \cos (2\pi f_0 n T_s + \phi) + w[n]$$  

(1)

Maximum-Likelihood (ML) approach for estimation of the vector of parameters $\theta = [A, f_0, \phi]$

Fundamental frequency estimation becomes:

$$\hat{f}_0 = \arg \max_f \left| \sum_{n=0}^{N-1} \bar{L}[n] e^{-j2\pi f n T_s} \right|^2$$  

(2)

Amplitude estimation: $\hat{A} = \frac{2}{N} \left| \sum_{n=0}^{N-1} \bar{L}[n] e^{-j2\pi \hat{f}_0 n T_s} \right|$

Absence/presence seizures threshold: $N \hat{A}^2 > \eta$
Detection of clonic seizures (2/2)

Periodic motion signal example

Periodogram

Periodogram of $\bar{L}_s[i]$

Motion signal $\bar{L}_s[i]$

$\hat{f}$: estimated frequency
Performance in seizures detection

- Detection system is investigated considering a binary test:
  - Sensitivity: $\alpha = \frac{n_{TP}}{n_{TP} + n_{FN}}$;  Specificity: $\beta = \frac{n_{TN}}{n_{TN} + n_{FP}}$
  - Receiver Operating Characteristic (ROC)

- Processing with temporal windows $NT_s = 10$ s, with 50% interlacing factor

- Performance evaluation on 10 video samples of 5 min duration with resolution $360 \times 288$ pixels, recorded at 25 Hz

<table>
<thead>
<tr>
<th></th>
<th>Real Positive</th>
<th>Real Negative</th>
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<tbody>
<tr>
<td>Positive test</td>
<td>$n_{TP} = 51$</td>
<td>$n_{FP} = 16$</td>
</tr>
<tr>
<td>Negative test</td>
<td>$n_{FN} = 7$</td>
<td>$n_{TN} = 210$</td>
</tr>
</tbody>
</table>

**Performance**

- $\alpha = 0.88$
- $\beta = 0.93$

**Table:** Detection of clonic seizures (one B&W camera).
Performance in seizure detection can be improved employing multiple sensors.

Multi-camera systems can see movements that may be covered for a single camera.

Extension of the periodicity model for $S$ sensors:

$$\bar{L}_s[n] = c_s + A_s \cos (2\pi f_0 n T_s + \phi_s) + w_s[n] \quad s \in \{1, 2, \ldots, S\}$$  \hspace{1cm} (3)

Data fusion for periodicity estimation:

$$\hat{f}_0 = \arg \max_f \sum_{s=1}^{S} \left| \sum_{n=0}^{N-1} \bar{L}_s[n] e^{-j2\pi fn T_s} \right|^2$$  \hspace{1cm} (4)

A significant periodic component is declared if a threshold $\eta$ is exceeded according to

$$\frac{N}{S} \sum_{s=1}^{S} \hat{A}^2 > \eta$$
Covered movements can be detected by camera sensors with different viewpoints.
Performance with multi-cam

- Processing with temporal windows $NT_s = 10$ s, with 50% interlacing factor

- Performance evaluation on 4 video samples of 1 min duration with resolution $360 \times 288$ pixels, recorded at 25 Hz

Performance evaluation on 4 video samples of 1 min duration with resolution $360 \times 288$ pixels, recorded at 25 Hz

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<td>Positive test</td>
<td>$n_{TP} = 50$</td>
<td>$n_{FP} = 9$</td>
</tr>
<tr>
<td>Negative test</td>
<td>$n_{FN} = 7$</td>
<td>$n_{TN} = 218$</td>
</tr>
<tr>
<td><strong>Performance</strong></td>
<td>$\alpha = 0.88$</td>
<td>$\beta = 0.96$</td>
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**Table:** Detection of clonic seizures (3 RGB cameras).

- Better performance by increasing the number of sensors involved
Application of depth sensor

- Depth information can be used to improve the ability of a standard video-based system to distinguish pathological movements from:
  1. background noise
  2. random movements not concerning the framed patient

- Performance evaluation on 2 video samples of 10 min duration with resolution $640 \times 480$ pixels, recorded at 30 Hz

- Issues: shadowing noise

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<tr>
<td>Positive test</td>
<td>$n_{TP} = 138$</td>
<td>$n_{FP} = 10$</td>
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<tr>
<td>Negative test</td>
<td>$n_{FN} = 12$</td>
<td>$n_{TN} = 78$</td>
</tr>
<tr>
<td>Performance</td>
<td>$\alpha = 0.92$</td>
<td>$\beta = 0.88$</td>
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**Table:** Detection of clonic seizures (1 camera + depth sensor [$S = 2$]).
- Selection of a part of the body to track (e.g. limbs)
- Feature selection as Most Interesting Motion Point (MIMP) by optical flow analysis
- Trajectories extraction by features tracking with template matching
- Similarity measure: Mean Absolute Difference (MAD)
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Issues on motion information extraction

- Extraction of a signal which describes the amount of breathing movement in a video recorded by an RGB camera
- The algorithm employed for large movements is inefficient

PROBLEM

Difficulty in the extraction of a reliable motion signal for small movements, such as the ones related to respiration
Issues on motion information extraction

- Extraction of a signal which describes the amount of breathing movement in a video recorded by an RGB camera.
- The algorithm employed for large movements is inefficient.

PROBLEM

Difficulty in the extraction of a reliable motion signal for small movements, such as the ones related to respiration.
Subtle motion magnification

- Eulerian Video Magnification (EVM):\(^1\)
  1. frame decomposition by Laplacian pyramid \(\{P_0, \ldots, P_{L-1}\}\)
  2. pixel-wise temporal filtering \(\{\Upsilon_0, \ldots, \Upsilon_{L-1}\}\)
  3. variable gain amplification \(\{\alpha_0, \ldots, \alpha_{L-1}\}\)
  4. video frame reconstruction

- Application of the motion extraction algorithm after the EVM processing

- ML approach:
  \[
  \begin{align*}
  \bar{L}[n] &= c + \cos(2\pi f_0 T_s n + \phi) + w[n] \\
  \hat{f}_0 &= \arg \max_f \| \text{DFT} \{ \bar{L}[n] \} \|_2^2
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---

Performance in apnea detection

- Applied on video recordings framing newborns for performance evaluation in the detection of apnea events.
- Analysis of the signal \( \bar{L}[n] \) is performed on half-interlaced windows with a time duration of \( NT_s = 20 \) s.
- Results are reported in terms of sensitivity (\( \alpha \)) and specificity (\( \beta \)), where:

\[
\alpha = \frac{T_{TP}}{T_{TP} + T_{FN}} \quad \beta = \frac{T_{TN}}{T_{TN} + T_{FP}}
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(5)

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</tr>
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<td>-------</td>
<td>----</td>
</tr>
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<td>worst</td>
<td>13</td>
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Legend: DA=number of Detected Apneas; \( T_{TP}, T_{TN}, T_{TP}, T_{FN} \) (s).

\(^2\)This algorithm is referred to as Motion Magnification for Apnea Detection (MMAD).
Performance in apnea detection

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This algorithm is referred to as Motion Magnification for Apnea Detection (MMAD).
Drawbacks (1/2)

- EVM is employed as a pre-processing system ⇒ video is processed two times
- The method for the extraction of motion signal is highly inefficient for periodical breathing movements:
  1. DoF ⇒ high-pass FIR filter with $H(f) = 1 - e^{-j2\pi f}$
  2. breathing frequencies of a newborn at rest ⇒ 18 – 60 bpm
EVM is employed as a pre-processing system ⇒ video is processed two times

Integration of EVM with motion analysis algorithm.

Solutions

- Integration of the EVM algorithm with the motion signal extraction algorithm
- Use of appropriate digital filters
Avoid to use the DoF filter in the extraction of $\bar{L}[n] \Rightarrow$ employ the temporal filters of the EVM

Avoid to reconstruct the overall pyramid for frame reconstruction $\Rightarrow$ employ the pyramidal levels

Frames processing for motion information extraction on pyramidal levels $\Rightarrow$ data fusion for RR estimation

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This algorithm is referred to as Spatio-Temporal video processing for RR estimation (STRE).
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Avoid to reconstruct the overall pyramid for frame reconstruction
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Performance in RR estimation

- RR estimated from $\{\overline{L}_\ell\}_{\ell=0}^{L-1}$ signals (employed for data fusion) are compared with rates estimated from pneumogram.

- According to medical practice, a tolerance of $\pm 15\%$ is considered.

**Example n.1**

![Graph showing performance in RR estimation](image-url)
Performance in RR estimation

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Example n.2
Exploiting pixel-wise variations

- Periodic pixel-wise variations can be exploited to analyze spatio-temporal movements of the framed patient.

- Pixel-wise variations can be modeled as

  \[ X[n] = C + A \cos(2\pi f_0 T s n + \Phi) + W[n] \]  

(6)

- ML approach to estimate the vector of parameters \( \theta = [a_v, f_0, \phi_v] \)
  (where \( s_v [n] = \text{vec} (S[n]) \))
The likelihood function becomes:

\[ J(\theta) = \sum_{p=0}^{M_1 M_2 - 1} \sum_{n=0}^{N-1} \left[ x_v[p, n] - a_v[n] \cos(2\pi f_0 T_s n + \phi_v[p]) \right]^2 \]  \hspace{1cm} (7)

Estimation of the fundamental frequency:

\[ \hat{f}_0 = \frac{f_s}{N} \arg \max_{k_{\min} \leq k \leq k_{\max}} \left| \sum_{p=0}^{M_1 M_2 - 1} \sum_{n=0}^{N-1} x_v[p, n] e^{-j2\pi \frac{k}{N} n} \right|^2 \] \hspace{1cm} (8)

Pixel-wise amplitudes may be estimated as:

\[ \hat{a}_v[p] = \frac{2}{N} \left| \sum_{n=0}^{N-1} x_v[p, n] e^{-j2\pi \hat{f}_0 T_s n} \right| \] \hspace{1cm} (9)

The ML approach can be both used to estimate the RR of the framed patient and select areas, inside the video frames, mainly affected by respiratory movements.
• Analysis of pixel-wise variations related to respiratory movements and estimate the RR of the framed patient:
  
  • Selection of $R$ areas (Regions Of Interest, ROI) involved in respiratory movements only
  
  • Large motion detection on ROI, which can compromise performance in the estimation of RR
  
  • Data fusion on multiple ROI to reinforce and improve RR estimation
  
  • Estimation is performed on temporal windows of $NT_s$ seconds
Pixel-wise ML video processing (2/2)

compute $\hat{A}$ and select ROI
The ML approach is applied to ROI, to reinforce estimation and avoid the interference of large movements.
The ML approach is applied to ROI, to reinforce estimation and avoid the interference of large movements.
Analysis of pixel variations

- The pixel-wise ML approach exploits temporal periodicity of pixels involved in respiratory movements

Example

Small movements near the throat can be also used to estimate the RR
Examples of RR estimation

- The algorithm can estimate the RR over time, monitoring continuously the framed patient.
Performance analysis

- The pixel-wise ML algorithm is compared with the "gold-standard" pneumogram and the STRE algorithm.
- Tests for the whole video and using a number of ROI $R = 4$.

Example n.1
The pixel-wise ML algorithm is compared with the “gold-standard” pneumogram and the STRE algorithm.

Tests for the whole video and using a number of ROI $R = 4$
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A non-trivial problem: the lack of databases of video recordings properly matched with reliable medical data:

- apnea events may be rare (CCHS or other syndromes)
- long records with simultaneous RR measurements and video streams may not be readily available

Detection and measurement algorithms must be designed, tested and reliable

Statistical models of RR patterns and of respiratory pauses/apnea events

Two models:
- respiratory pauses/apnea events
- complete RR patterns

Simulators:
- software-based
- hardware-based

Continuous-Time Markov Chains (CTMC)-based statistical models

In-depth tests of developed video processing-based algorithms
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In-depth tests of developed video processing-based algorithms
Apnea is defined as an absence of respiration of at least 20 s, or 10 s if associated with other symptoms.

Apnea events can be related to severe dysfunctions (Obstruction Sleep Apnea Syndrome [OSAS] or congenital diseases as Congenital Central Hypoventilation Syndrome [CCHS]).

Event based statistical model: two-state Markov chain

- $S_0 = \{\text{apnea event}\}$
- $S_1 = \{\text{regular breathing}\}$
- $b_i = \{\text{duration of apnea}\}$
- $a_i = \{\text{duration of regular breathing}\}$
- Model parameters: $b_i \sim \exp(\mu)$, $a_i \sim \exp(\nu)$
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- \( S_1 = \{ \text{regular breathing} \} \)
- \( b_i = \{ \text{duration of apnea} \} \)
- \( a_i = \{ \text{duration of regular breathing} \} \)
- model parameters: \( b_i \sim \exp(\mu), a_i \sim \exp(\nu) \)
- RR of a newborn (at rest): 0.3–1.1 Hz (18–66 bpm)

- The two-state model is extended to $N$ state, where each state \( \{S_n\}_{n=0}^{N-1} \) represents the RR \( \{\varrho_n\}_{n=0}^{N-1} \) and the order \( \varrho_0 < \ldots < \varrho_{N-1} \) is assumed

- States \( \{S_n\}_{n=0}^{N-1} \) are properly assigned depending on the presence of apnea events and large random movements

- The CTMC model is characterized by the inter-arrival times $\tau_\ell \sim \exp(\mu_n)$ and from the infinitesimal generator matrix $\Lambda$
Estimation of model parameters

Two-state model

- The mean duration of apnea events and of regular breathing can be estimated from clinical evaluations or pneumographic signals.
- Average values may be set as: $\mathbb{E}\{a_i\} = 1/\nu$, $\mathbb{E}\{b_i\} = 1/\mu$
- Parameters of the CTMC model are simply estimated.

Extended $N$-state model

- Real RR are estimated from recorded pneumographic signals.
- Rates $\{\varrho_n\}_{n=0}^{N-1}$ are selected by Lloyd-Max\(^4\) quantization to $N$ levels.
- Transition rates and infinitesimal generator matrix are obtained by ML estimator: $\hat{\Lambda}$, where $\hat{\lambda}_{m,n} = \frac{N_{m,n}(T)}{R_n(T)} \geq 0$

---

Extended $N$-state model

- Real RR are estimated from recorded pneumographic signals
- Rates $\{\varrho_n\}_{n=0}^{N-1}$ are selected by Lloyd-Max\textsuperscript{4} quantization to $N$ levels
- Transition rates and infinitesimal generator matrix are obtained by ML estimator: $\hat{\Lambda}$, where $\hat{\lambda}_{m,n} = \frac{N_{m,n}(T)}{R_n(T)} \geq 0$

Simulators

Software-based simulator

- Interpolation and decimation of video frames in order to accelerate or slow down breathing movements
- Noise compensation algorithm to maintain background noise

Hardware-based simulator

- Able to replicate breathing movements of the chest
- Based on Arduino UNO board to drive the DC step motor which move part of the chest
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Riccardo Raheli (University of Parma)
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Simulation of apnea events

- (a) normal breathing pattern [original video]
- (b) software-simulated respiratory pause
- (c) real respiratory pause
Simulation of breathing patterns

$n = 5$

Apnea or respiratory pause

$\varphi_0 = 0$ Hz  $\varphi_1 = 0.38$ Hz  $\varphi_2 = 0.69$ Hz  $\varphi_3 = 0.99$ Hz  $\varphi_4 = 1.3$ Hz
Performance by simulated patterns

Performance for the detection of apnea events with two algorithms: **MMAD** and **STRE**

Performance is measured in terms of:

- Receiver Operating Characteristics (ROC)
- sensitivity ($\alpha$) and specificity ($\beta$)
- Area Under Curve (AUC)
- Diagnostic Odds Ratio $\Delta = \frac{\alpha}{1-\alpha} \cdot \frac{\beta}{1-\beta}$

(a) performance for *software-based* simulator

(b) performance for *hardware-based* simulator
Performance by simulated patterns

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<table>
<thead>
<tr>
<th>Algorithm</th>
<th>$\alpha$</th>
<th>$\beta$</th>
<th>$\Delta$</th>
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<tbody>
<tr>
<td>MMAD</td>
<td>0.888</td>
<td>0.829</td>
<td>38.4</td>
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<tr>
<td>STRE</td>
<td>0.91</td>
<td>0.869</td>
<td>67.1</td>
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(a) Detection performance for software-based simulator.

<table>
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</tr>
</thead>
<tbody>
<tr>
<td>MMAD</td>
<td>0.951</td>
<td>0.787</td>
<td>71.7</td>
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<tr>
<td>STRE</td>
<td>0.923</td>
<td>0.896</td>
<td>103.3</td>
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</table>

(b) Detection performance for hardware-based simulator.
Hardware simulation of seizure events

Clonic seizures

Tonic seizures

DC MOTOR
Outline

1. Introduction
2. Detection of seizures
3. Monitoring of respiration and its disorders
4. Simulators of neonatal disorders
5. **Mobile application: smartCED**
6. Conclusion
Smartphone Based Contactless Epilepsy Detector

Android application for neonatal seizures detection
Laboratory test with seizure simulator.
SmartCED app: ROI selection

a) Selezione diagonale del rettangolo sul quadro originale

b) Maschera rettangoloare M[i]

c) Rappresentazione matrici dele del quadro originale Y[i]

d) Z[i] = M[i] and Y[i]

e) Z[i] risultante sullo schermo
SmartCED app: multiple sights

a) Pop-up menu – visione multipla

b) Scala di grigio/Single diff

c) Scala di grigio/Double diff

d) Single diff/Double diff
SmartCED app: crisis database

- Count the number of epileptic crises
- Save starting and ending time of the detected event
- Display the duration of each single event
- Show the city where the event is detected
SmartCED app: geo-localization

France
Number of Crisis: 7
Conclusions

- Algorithms for remote monitoring of newborns
- Periodicity analysis applied to the detection of seizures, apneas and monitoring of RR
- Statistical models of apneas and breathing patterns based on CTMCs useful to devise simulators
- Development of software- and hardware-based simulators to test video processing-based algorithms
- Mobile Android APP for neonatal seizure detection

Future work

- Extension to other vital signs (e.g. heart rate)
- Development of portable contactless devices to monitor patient on single-board computers
- Improvement of the statistical models by taking into account other conditions
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UNIVERSITÀ DI PARMA
DEPARTMENT OF ENGINEERING AND ARCHITECTURE
DEPARTMENT OF MEDICINE AND SURGERY

Riccardo Raheli (University of Parma)