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

University of Parma

Department of Engineering and Architecture (Information Engineering)

Department of Medicine and Surgery

Venice (Italy), April 23th, 2017

Outline

Outline

UNIVERSITÀ DI PARMA

Neonatal diseases

UNIVERSITÀ DI PARMA

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

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

Systems for patient monitoring

UNIVERSITÀ DI PARMA

Seizures and nervous system diseases:

- Based on EEG, ECG and EMG systems

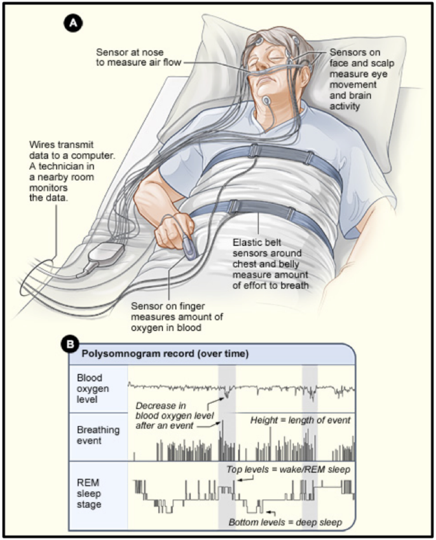
Respiration and apnea events:

- 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

Seizures and nervous system diseases:

- Based on EEG, ECG and EMG systems

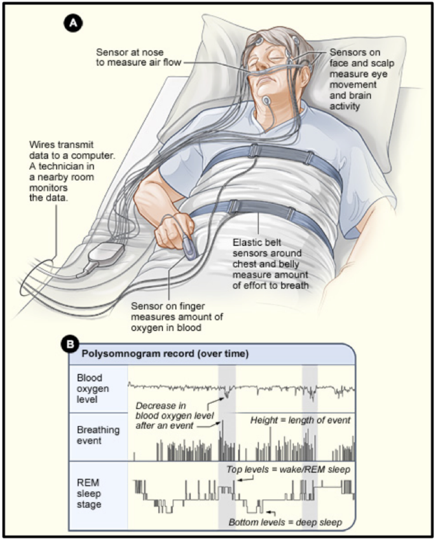
Respiration and apnea events:

- 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

Systems for patient monitoring

UNIVERSITÀ DI PARMA

Seizures and nervous system diseases:

- Based on EEG, ECG and EMG systems

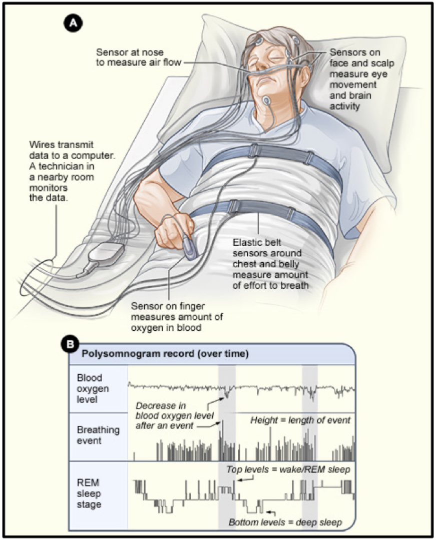
Respiration and apnea events:

- 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



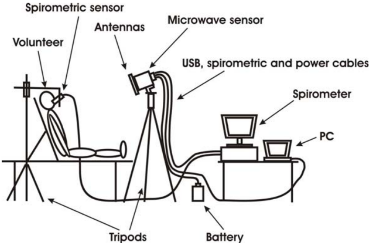
Sleep Apnea Guide (2016), The polysomnogram test [Online].

These devices are expensive and moderately invasive

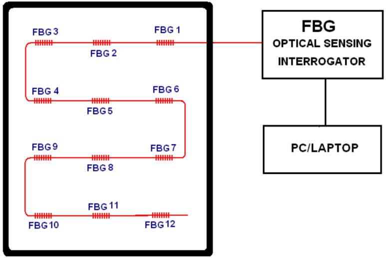
- Microwave radar sensors
- Fiber optic sensors (e.g., integrated in "smart bed")
- Networks of wireless sensors (e.g., WSNs around the patient)
- Wearable devices and smart-watches (e.g., smart sensors or clothing)

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.

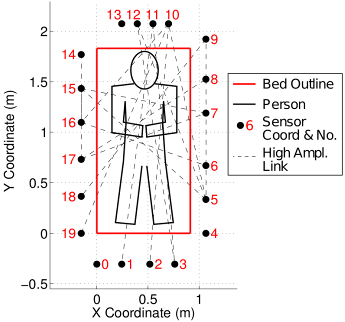


V. Mishra and N. Singh, "Optical fiber gratings in perspective of their applications in biomedicine," Biomedicine, InTech, 2012.

- 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.



N. Patwari *et al.*, “Monitoring breathing via signal strength in wireless networks,” IEEE Trans. Mobile Comput., 2014.

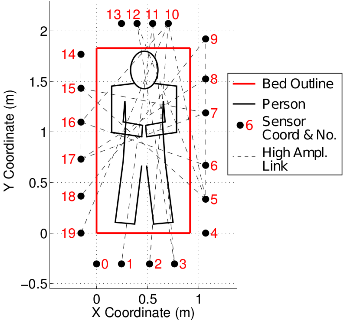
S. Bouwstra *et al.*, “Smart jacket design for neonatal monitoring with wearable sensors,” 6th Int. Workshop Wearable and Implantable Body Sensor Netw., 2009.

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.

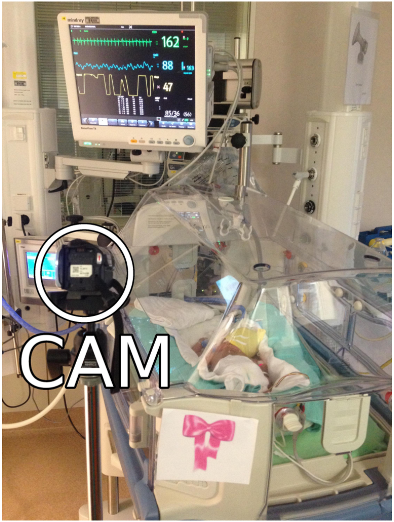


N. Patwari *et al.*, "Monitoring breathing via signal strength in wireless networks," IEEE Trans. Mobile Comput., 2014.

S. Bouwstra *et al.*, "Smart jacket design for neonatal monitoring with wearable sensors," 6th Int. Workshop Wearable and Implantable Body Sensor Netw., 2009.

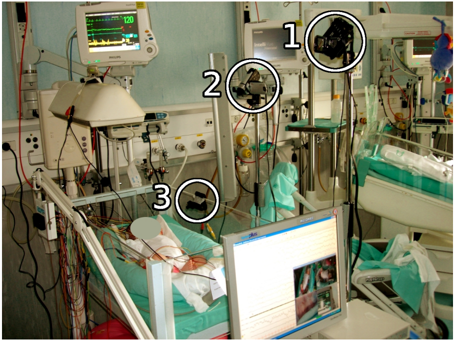
Video-processing based methods

- 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

- 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



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.,† Merrill S. Wise,†‡ Richard A. Hrachovy,†§ and Eli M. Mizrahi†‡*

Epilepsia (Wiley) 2006

Early work

UNIVERSITÀ DI PARMA

- 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

890 IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL. 14, NO. 7, JULY 2005

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

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

676 IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING, VOL. 52, NO. 4, APRIL 2005

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

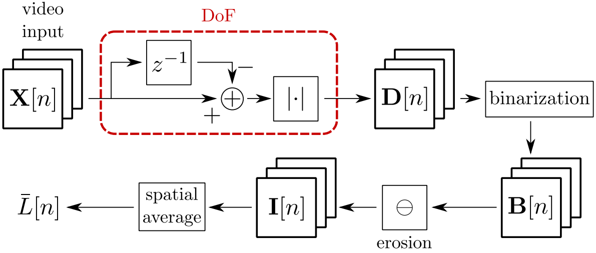
Early work

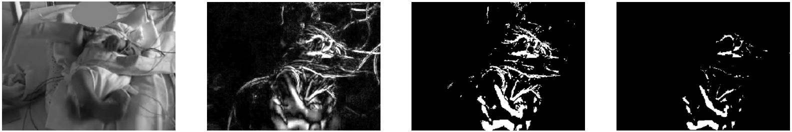
- N. B. Karayiannis *et al.*: **pioneering work** on the subject of seizure detection and analysis of newborns' movements by video cameras
  - Based on motion tracking of the limbs (e.g., optical flow, block motion models, template matching)
  - Use of neural networks (NNs) for event detection and motion 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

Need for fast, straightforward and reliable algorithms for real-time analysis of newborns' movements to promptly detect possible disorders

Outline

Motion information extraction (1/2)



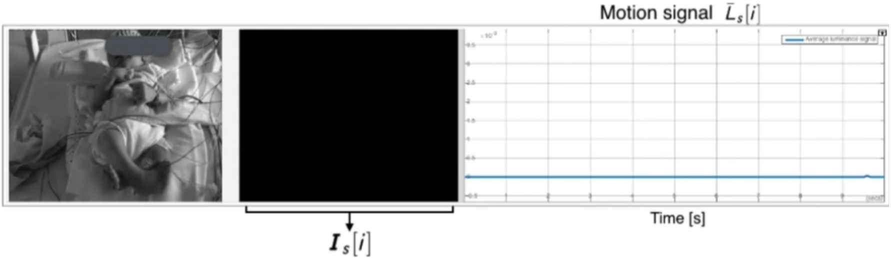


(a) gray-scale (b) DoF (c) binarization (d) erosion

- 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

Motion information extraction (2/2)

- 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

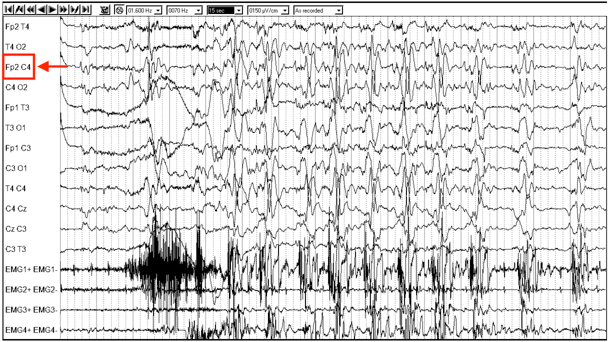


Example of clonic seizure in a newborn

Motion information extraction (2/2)

UNIVERSITÀ DI PARMA

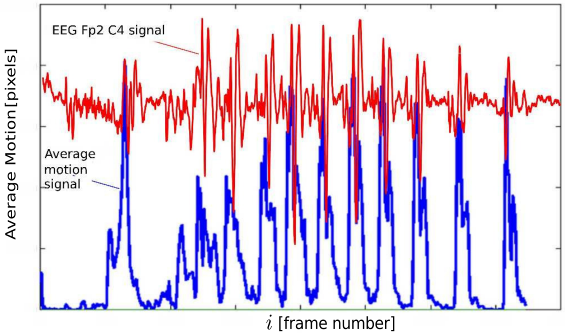
- Seizures are characterized by specific movements of limbs or body parts
- **Clonic seizures**: periodic movements with a repetition time between 0.5–2.5 s



- Extracted periodic movements correspond to an epileptic event in the EEG with comparable periodicity

Motion information extraction (2/2)

- 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



- Extracted periodic movements correspond to an epileptic event in the EEG with comparable periodicity

Detection of clonic seizures (1/2)

- **Clonic seizures detection by periodicity analysis**
- Model of periodicity in the motion signal $\bar{L}[n]$:

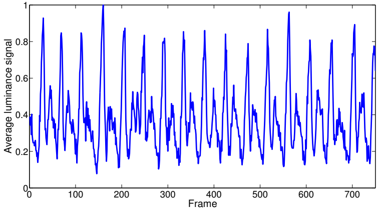
$$\bar{L}[n] = c + A\cos(2\pi f_0 n T_s + \phi) + w[n] \quad (1)$$

- Maximum-Likelihood (ML) approach for estimation of the vector of parameters $\boldsymbol{\theta} = [A, f_0, \phi]$
- Fundamental frequency estimation becomes:

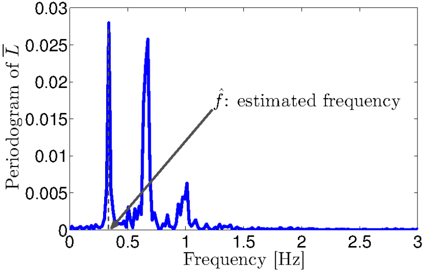
$$\hat{f}_0 = \arg\max_f \left| \sum_{n=0}^{N-1} \bar{L}[n] e^{-j2\pi f n T_s} \right|^2 \quad (2)$$

- 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: $N\hat{A}^2 > \eta$

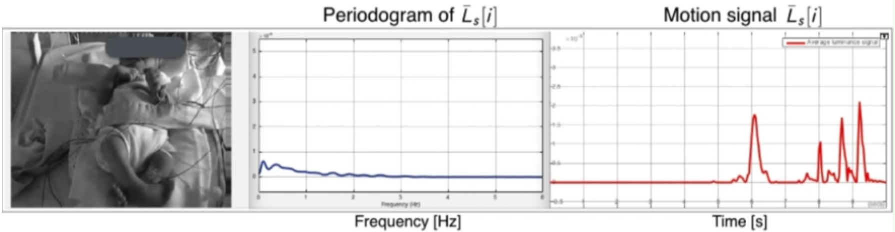
Detection of clonic seizures (2/2)



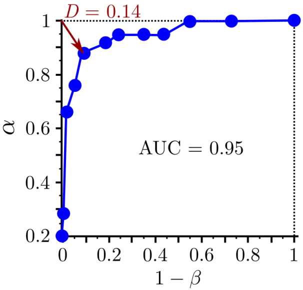
Periodic motion signal example



Periodogram



- Detection system is investigated considering a *binary test*:
  - Sensitivity: $\alpha = \frac{n_{\mathrm{TP}}}{n_{\mathrm{TP}}+n_{\mathrm{FN}}}$; Specificty: $\beta = \frac{n_{\mathrm{TN}}}{n_{\mathrm{TN}}+n_{\mathrm{FP}}}$
  - 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 360×288 pixels, recorded at 25 Hz



	Real Positive	Real Negative
Positive test	$n_{\mathrm{TP}} = 51$	$n_{\mathrm{FP}} = 16$
Negative test	$n_{\mathrm{FN}} = 7$	$n_{\mathrm{TN}} = 210$
Performance	$\alpha = 0.88$	$\beta = 0.93$

Table: Detection of clonic seizures (one B&W camera).

Extension to multiple sensors (1/2)

- 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

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

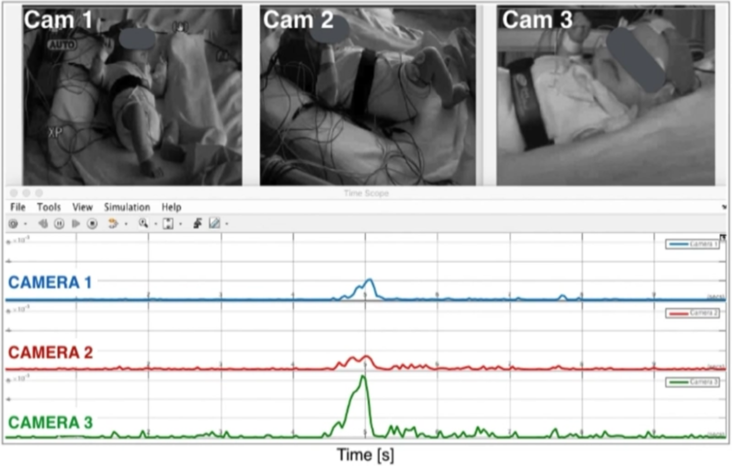
- Data fusion for periodicity estimation

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

- A significant periodic component is declared if a threshold η is exceeded according to $\frac{N}{S} \sum_{s=1}^{S} \hat{A}^2 > \eta$

Extension to multiple sensors (2/2)

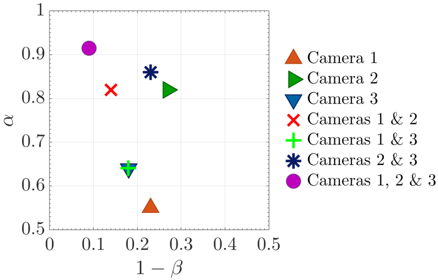
- Covered movements can be detected by camera sensors with different viewpoints



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

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 360×288 pixels, recorded at 25 Hz



	Real Positive	Real Negative
Positive test	$n_{\mathrm{TP}} = 50$	$n_{\mathrm{FP}} = 9$
Negative test	$n_{\mathrm{FN}} = 7$	$n_{\mathrm{TN}} = 218$
Performance	$\alpha = 0.88$	$\beta = 0.96$

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 640×480 pixels, recorded at 30 Hz
- Issues: **shadowing noise**

	Real Positive	Real Negative
Positive test	$n_{\mathrm{TP}} = 138$	$n_{\mathrm{FP}} = 10$
Negative test	$n_{\mathrm{FN}} = 12$	$n_{\mathrm{TN}} = 78$
Performance	$\alpha = 0.92$	$\beta = 0.88$

Table: Detection of clonic seizures (1 camera + depth sensor [$S = 2$]).

Tracking of movements

- 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)

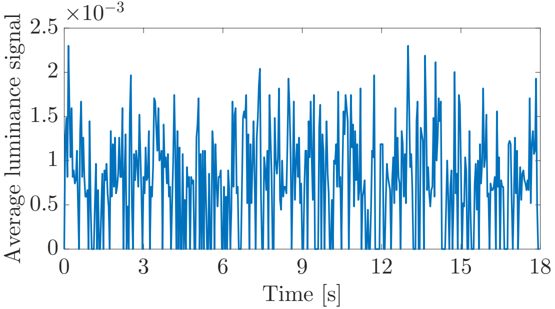
Outline

UNIVERSITÀ DI PARMA

Issues on motion information extraction

UNIVERSITÀ DI PARMA

- 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**



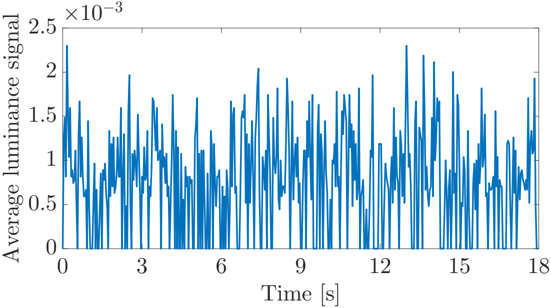
PROBLEM

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

Issues on motion information extraction

UNIVERSITÀ DI PARMA

- 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**



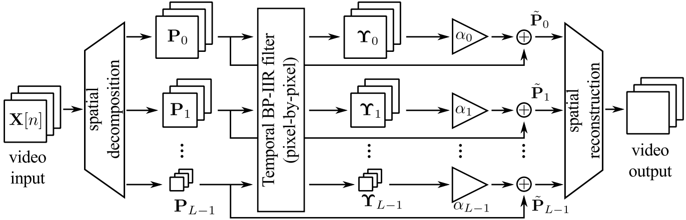
PROBLEM

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

Subtle motion magnification

UNIVERSITÀ DI PARMA

- Eulerian Video Magnification (EVM):[1]
  1. frame decomposition by Laplacian pyramid $\{\mathbf{P}_0, \ldots, \mathbf{P}_{L-1}\}$
  2. pixel-wise temporal filtering $\{\boldsymbol{\Upsilon}_0, \ldots, \boldsymbol{\Upsilon}_{L-1}\}$
  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: $\begin{cases} \bar{L}[n] = c + \cos(2\pi f_0 T_s n + \phi) + w[n] \\ \hat{f}_0 = \arg\max_f \|\text{DFT}\left\{\bar{L}[n]\right\}\|^2 \end{cases}$



[1] Wu, Rubinstein, Shih, Guttag, Durand, Freeman, "Eulerian video magnification for revealing subtle changes in the world," ACM. Trans. Graph., vol. 31, no. 4, pp. 65:1–65:8, July 2012.

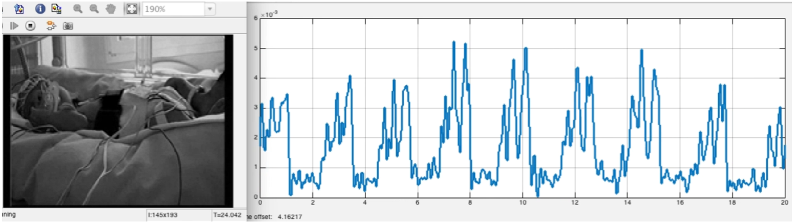
Subtle motion magnification

- Eulerian Video Magnification (EVM):[1]
  1. frame decomposition by Laplacian pyramid $\{\mathbf{P}_0, \ldots, \mathbf{P}_{L-1}\}$
  2. pixel-wise temporal filtering $\{\boldsymbol{\Upsilon}_0, \ldots, \boldsymbol{\Upsilon}_{L-1}\}$
  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: $\begin{cases} \bar{L}[n] = c + \cos(2\pi f_0 T_s n + \phi) + w[n] \\ \hat{f}_0 = \arg\max_f \|\mathrm{DFT}\left\{\bar{L}[n]\right\}\|^2 \end{cases}$

[1] Wu, Rubinstein, Shih, Guttag, Durand, Freeman, "Eulerian video magnification for revealing subtle changes in the world," ACM. Trans. Graph., vol. 31, no. 4, pp. 65:1–65:8, July 2012.

Subtle motion magnification

- Eulerian Video Magnification (EVM):[1]
  1. frame decomposition by Laplacian pyramid $\{\mathbf{P}_0, \ldots, \mathbf{P}_{L-1}\}$
  2. pixel-wise temporal filtering $\{\boldsymbol{\Upsilon}_0, \ldots, \boldsymbol{\Upsilon}_{L-1}\}$
  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: $\begin{cases} \bar{L}[n] = c + \cos(2\pi f_0 T_s n + \phi) + w[n] \\ \hat{f}_0 = \arg\max_f \|\mathrm{DFT}\left\{\bar{L}[n]\right\}\|^2 \end{cases}$



[1] Wu, Rubinstein, Shih, Guttag, Durand, Freeman, "Eulerian video magnification for revealing subtle changes in the world," ACM. Trans. Graph., vol. 31, no. 4, pp. 65:1–65:8, July 2012.

Performance in apnea detection[2]

- 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 (α) and specificity (β), where:

$$\alpha = \frac{T_{\text{TP}}}{T_{\text{TP}} + T_{\text{FN}}} \qquad \beta = \frac{T_{\text{TN}}}{T_{\text{TN}} + T_{\text{FP}}} \tag{5}$$

Performance in apnea detection

case	DA	T_{TP}	T_{TN}	T_{FP}	T_{FN}	α	β
worst	13	1200	1800	500	140	0.90	0.78
best	17	1340	1920	380	0	1.00	0.83

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[2]

- 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 (α) and specificity (β), where:

$$\alpha = \frac{T_{\mathrm{TP}}}{T_{\mathrm{TP}} + T_{\mathrm{FN}}} \qquad \beta = \frac{T_{\mathrm{TN}}}{T_{\mathrm{TN}} + T_{\mathrm{FP}}} \tag{5}$$

Performance in apnea detection

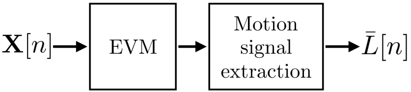
case	DA	T_{TP}	T_{TN}	T_{FP}	T_{FN}	α	β
worst	13	1200	1800	500	140	0.90	0.78
best	17	1340	1920	380	0	1.00	0.83

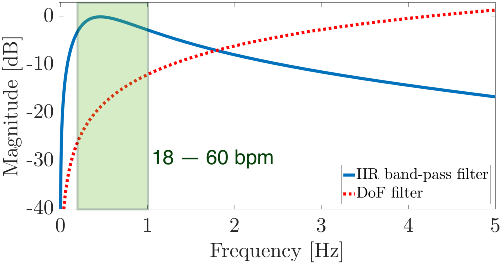
Legend: DA=number of Detected Apneas; T_{TP}, T_{TN}, T_{TP}, T_{FN} (s).

[2] This algorithm is referred to as Motion Magnification for Apnea Detection (**MMAD**).

Drawbacks (1/2)

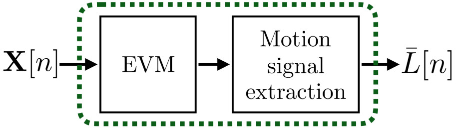
- EVM is employed as a pre-processing system ⇒ video is processed two times
- The method for the extraction of motion signal is highly inefficient for periodical breathing movements:
  1. DoF ⇒ high-pass FIR filter with $H(f) = 1 - e^{-j2\pi f}$
  2. breathing frequencies of a newborn at rest ⇒ 18 –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





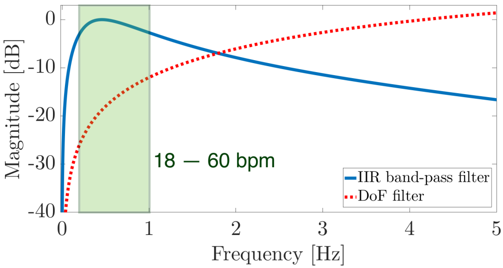
- EVM is employed as a pre-processing system ⇒ video is processed two times

Integration of EVM with motion analysis algorithm.

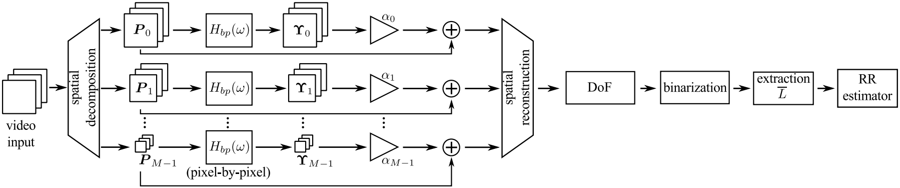


Solutions

- Integration of the EVM algorithm with the motion signal extraction algorithm
- Use of appropriate digital filters



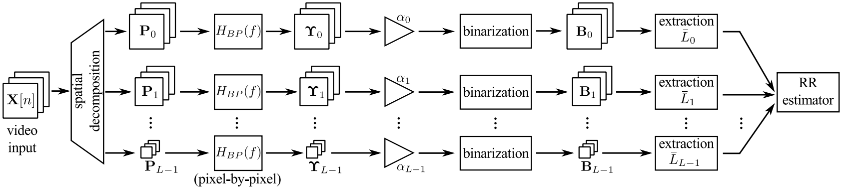
Spatio-temporal RR estimation[3]



- 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

[3] This algorithm is referred to as Spatio-Temporal video processing for RR estimation (**STRE**).

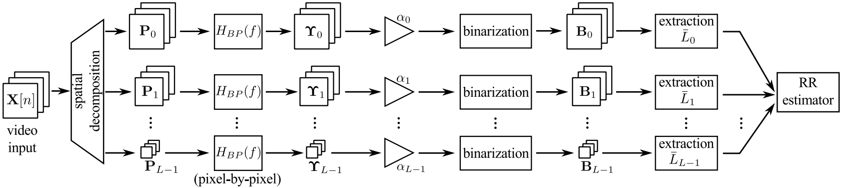
Spatio-temporal RR estimation[3]

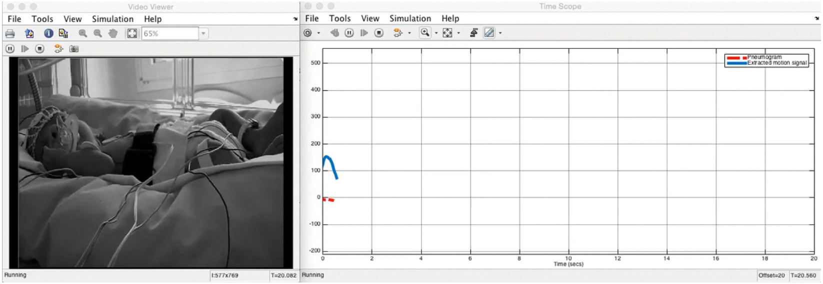


- Avoid to use the DoF filter in the extraction of $\bar{L}[n] \Rightarrow$ employ the temporal filters of the EVM
- Avoid to reconstruct the overall pyramid for frame reconstruction $\Rightarrow$ employ the pyramidal levels
- Frames processing for motion information extraction on pyramidal levels $\Rightarrow$ data fusion for RR estimation

[3] This algorithm is referred to as Spatio-Temporal video processing for RR estimation (**STRE**).

Spatio-temporal RR estimation[3]

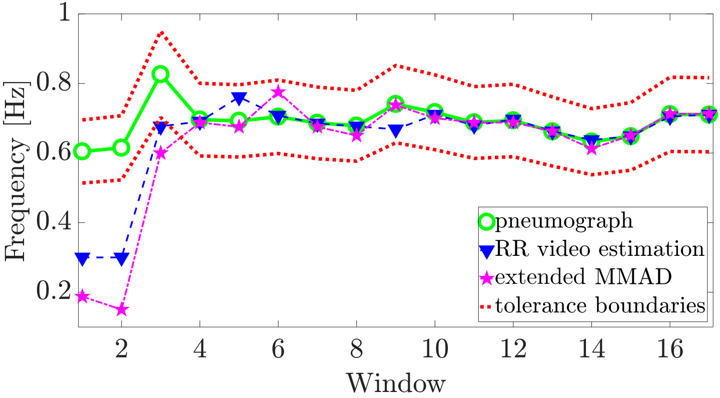




[3]This algorithm is referred to as Spatio-Temporal video processing for RR estimation (**STRE**).

Performance in RR estimation

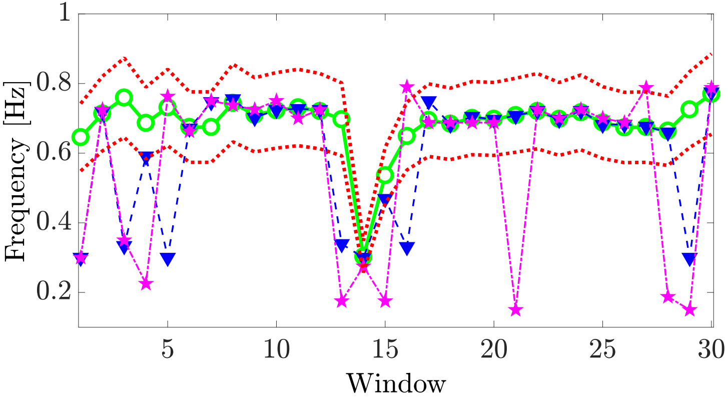
- RR estimated from $\{\bar{L}_\ell\}_{\ell=0}^{L-1}$ signals (employed for data fusion) are compared with rates estimated from pneumogram.
- According to medical practice, a tolerance of $\pm 15\%$ is considered.



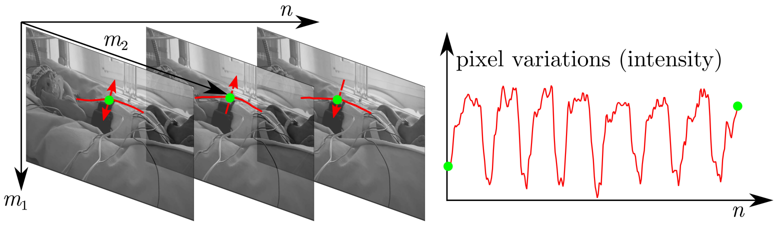
Example n.1

Performance in RR estimation

- RR estimated from $\{\bar{L}_\ell\}_{\ell=0}^{L-1}$ 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.2



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

$$\mathbf{X}[n] = \mathbf{C} + \mathbf{A}\cos(2\pi f_0 T_s n + \mathbf{\Phi}) + \mathbf{W}[n] \quad (6)$$

- ML approach to estimate the vector of parameters $\boldsymbol{\theta} = [\mathbf{a}_{\mathrm{v}}, f_0, \phi_{\mathrm{v}}]$ (where $\mathbf{s}_{\mathrm{v}}[n] = \mathrm{vec}(\mathbf{S}[n])$)

- The likelihood function becomes:

$$J(\boldsymbol{\theta}) = \sum_{p=0}^{M_1 M_2 - 1} \sum_{n=0}^{N-1} \left[x_{\mathrm{v}}[p,n] - a_{\mathrm{v}}[n] \cos\left(2\pi f_0 T_s n + \phi_{\mathrm{v}}[p]\right) \right]^2 \quad (7)$$

- Estimation of the fundamental frequency:

$$\hat{f}_0 = \frac{f_s}{N} \underset{k_{\min} \leq k \leq k_{\max}}{\arg\max} \sum_{p=0}^{M_1 M_2 - 1} \left| \sum_{n=0}^{N-1} x_{\mathrm{v}}[p,n] e^{-j2\pi \frac{k}{N} n} \right|^2 \quad (8)$$

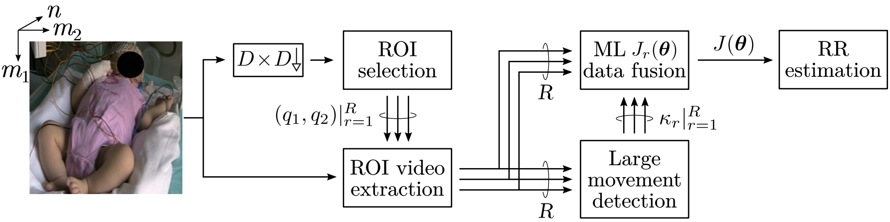
- Pixel-wise amplitudes may be estimated as:

$$\hat{a}_{\mathrm{v}}[p] = \frac{2}{N} \left| \sum_{n=0}^{N-1} x_{\mathrm{v}}[p,n] e^{-j2\pi \hat{f}_0 T_s n} \right| \quad (9)$$

- 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

Pixel-wise ML video processing (1/2)

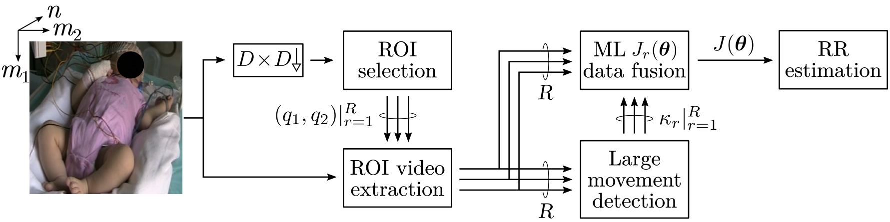
UNIVERSITÀ DI PARMA

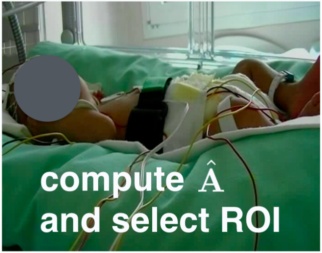


- Analysis of pixel-wise variations related to respiratory movements and estimate the RR of the framed patient:
  - Selection of R areas (Regions Of Interest, ROI) involved in respiratory movements only
  - Large motion detection on ROI, which can compromise performance in the estimation of RR
  - Data fusion on multiple ROI to reinforce and improve RR estimation
  - Estimation is performed on temporal windows of NT_s seconds

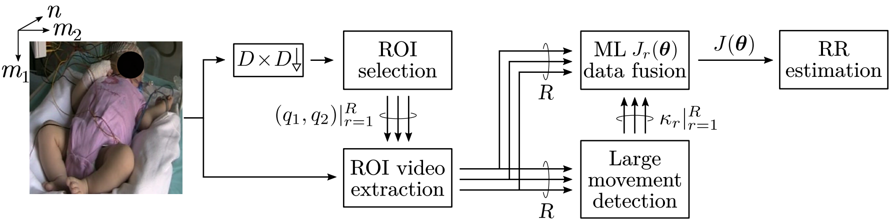
Pixel-wise ML video processing (2/2)

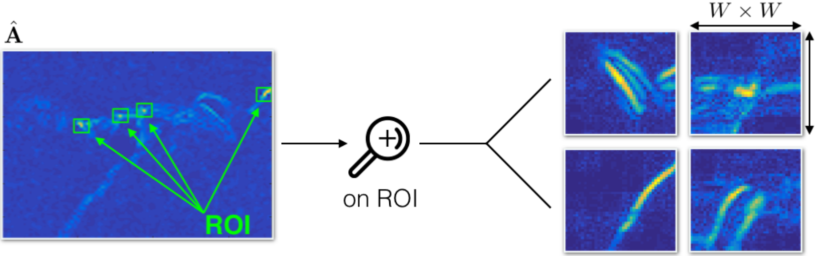
UNIVERSITÀ DI PARMA





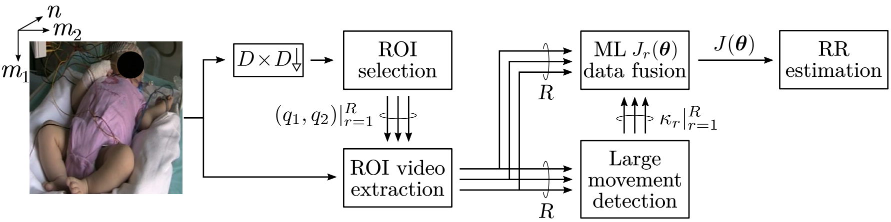
Pixel-wise ML video processing (2/2)

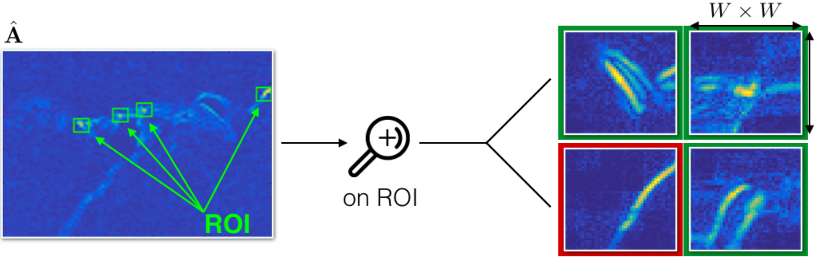




- The ML approach is applied to ROI, to reinforce estimation and avoid the interference of large movements

Pixel-wise ML video processing (2/2)

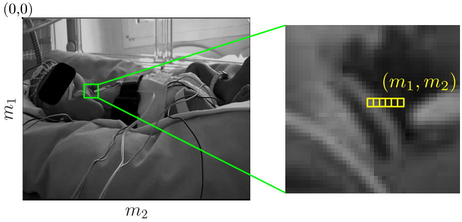


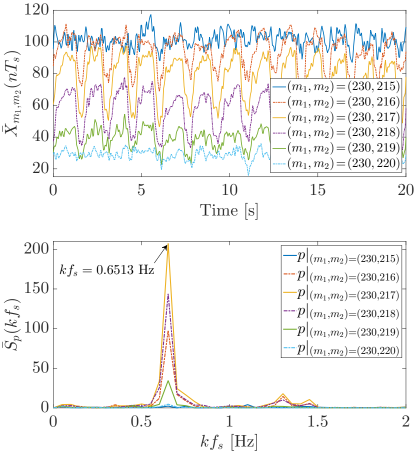


- The ML approach is applied to ROI, to reinforce estimation and avoid the interference of large movements

Analysis of pixel variations

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

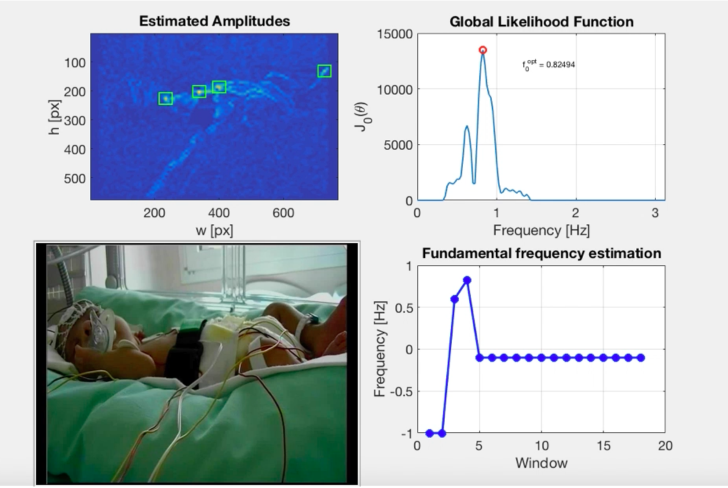




Example

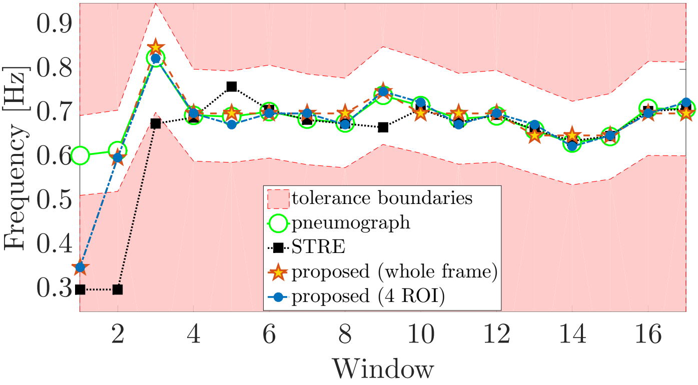
Small movements near the throat can be also used to estimate the RR

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



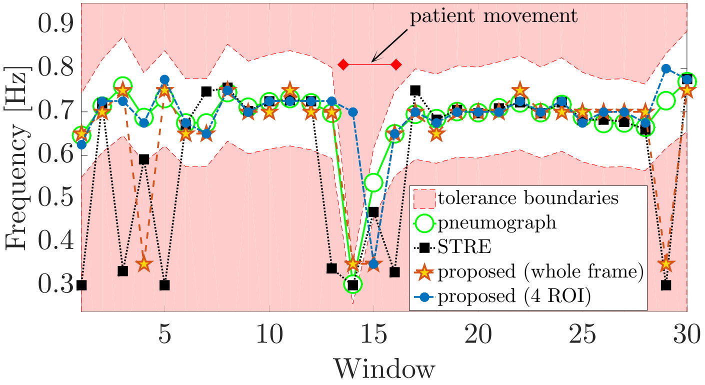
UNIVERSITÀ DI PARMA

- 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 $R = 4$



Example n.2

Outline

Analysis and design of RR estimators

- 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

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

Simulators:

- software-based
- hardware-based

In-depth tests of developed video processing-based algorithms

Analysis and design of RR estimators

UNIVERSITÀ DI PARMA

- 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

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

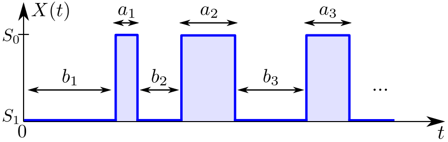
Simulators:

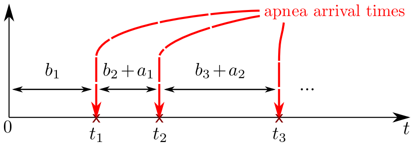
- software-based
- hardware-based

In-depth tests of developed video processing-based algorithms

Model of apnea episodes

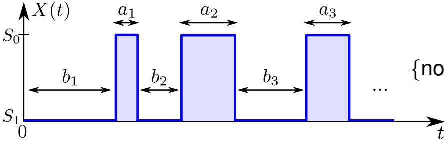
- Apnea is defined as an absence of respiration of at least 20 s, or 10 s if associated with other symptoms
- Apnea events can be related to severe dysfunctions (Obstruction Sleep Apnea Syndrome [OSAS] or congenital diseases as Congenital Central Hypoventilation Syndrome [CCHS])
- Event based statistical model: two-state Markov chain
  - $S_0 = \{$apnea event$\}$ $S_1 = \{$regular breathing$\}$
  - $b_i = \{$duration of apnea$\}$ $a_i = \{$duration of regular breathing$\}$
  - model parameters: $b_i \sim \exp(\mu)$, $a_i \sim \exp(\nu)$

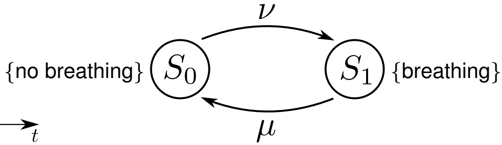




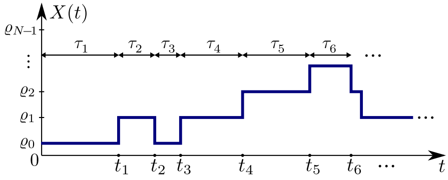
Model of apnea episodes

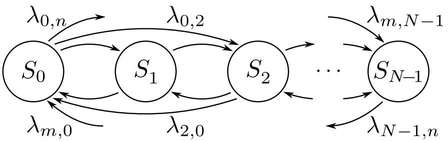
- Apnea is defined as an absence of respiration of at least 20 s, or 10 s if associated with other symptoms
- Apnea events can be related to severe dysfunctions (Obstruction Sleep Apnea Syndrome [OSAS] or congenital diseases as Congenital Central Hypoventilation Syndrome [CCHS])
- Event based statistical model: two-state Markov chain
  - $S_0 = \{\text{apnea event}\}$ $\quad S_1 = \{\text{regular breathing}\}$
  - $b_i = \{\text{duration of apnea}\}$ $\quad a_i = \{\text{duration of regular breathing}\}$
  - 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 $\mathbf{\Lambda}$





Estimation of model parameters

Two-state model

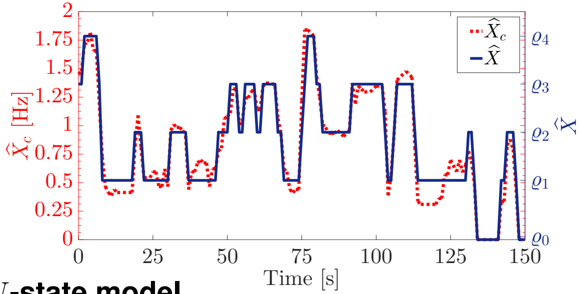
- The mean duration of apnea events and of regular breathing can be estimated from clinical evaluations or pneumographic signals
- Average values may be set as: $\mathbb{E}\{a_i\} = 1/\nu$, $\mathbb{E}\{b_i\} = 1/\mu$
- Parameters of the CTMC model are simply estimated

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: $\hat{\mathbf{\Lambda}}$, where $\hat{\lambda}_{m,n} = \frac{N_{m,n}(T)}{R_n(T)} \geq 0$

[4] S. Lloyd, "Least squares quantization in PCM", IEEE Trans. Inf. Theory, vol. 28, no. 2, 1982

Estimation of model parameters



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: $\hat{\mathbf{\Lambda}}$, where $\hat{\lambda}_{m,n} = \frac{N_{m,n}(T)}{R_n(T)} \geq 0$

[4] S. Lloyd, "Least squares quantization in PCM", IEEE Trans. Inf. Theory, vol. 28, no. 2, 1982

Simulators

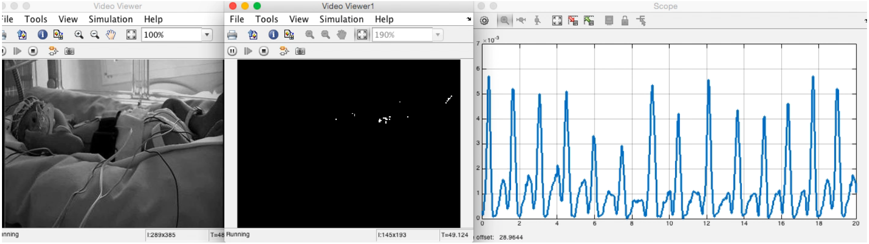
UNIVERSITÀ DI PARMA

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

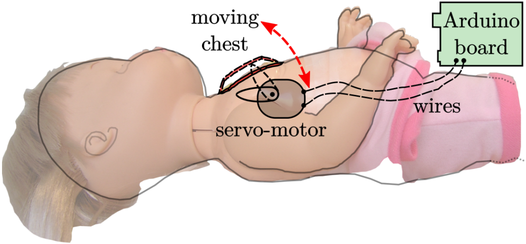


Software-based simulator

- 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



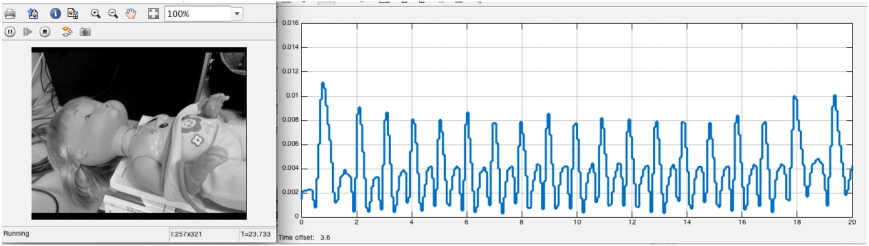
Simulators

Software-based simulator

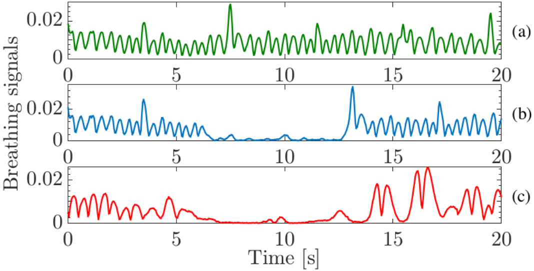
- Interpolation and decimation of video frames in order to accelerate or slow down breathing movements
- Noise compensation algorithm to maintain background noise

Hardware-based simulator

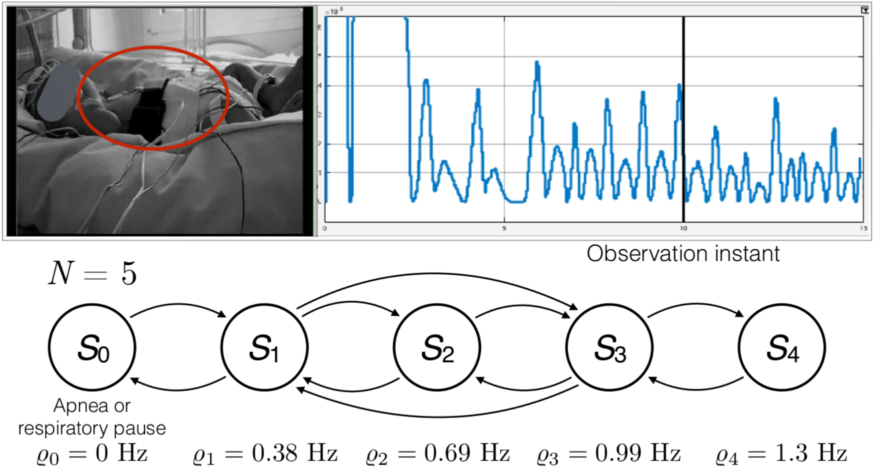
- Able to replicate breathing movements of the chest
- Based on Arduino UNO board to drive the DC step motor which move part of the chest



Simulation of apnea events



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

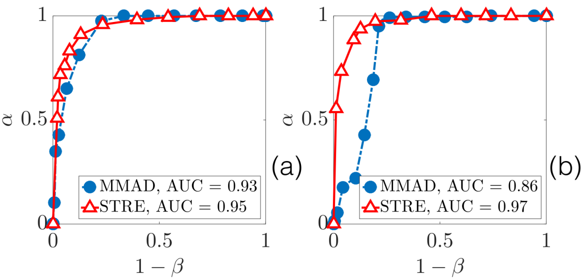

Observation instant
$N = 5$
S_0
S_1
S_2
S_3
S_4
Apnea or
respiratory pause
$\varrho_0 = 0$ Hz
$\varrho_1 = 0.38$ Hz
$\varrho_2 = 0.69$ Hz
$\varrho_3 = 0.99$ Hz
$\varrho_4 = 1.3$ Hz

Performance by simulated patterns

UNIVERSITÀ DI PARMA

- Performance for the detection of apnea events with two algorithms: **MMAD** and **STRE**
- Performance is measured in terms of:
  - Receiver Operating Characteristics (ROC)
  - sensitivity (α) and specificity (β)
  - 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

- Performance for the detection of apnea events with two algorithms: **MMAD** and **STRE**
- Performance is measured in terms of:
  - Receiver Operating Characteristics (ROC)
  - sensitivity (α) and specificity (β)
  - 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

Algorithm	α	β	Δ
MMAD	0.888	0.829	38.4
STRE	0.91	0.869	67.1

(a) Detection performance for software-based simulator.

Algorithm	α	β	Δ
MMAD	0.951	0.787	71.7
STRE	0.923	0.896	103.3

(b) Detection performance for hardware-based simulator.

Hardware simulation of seizure events

Clonic seizures

Tonic seizures

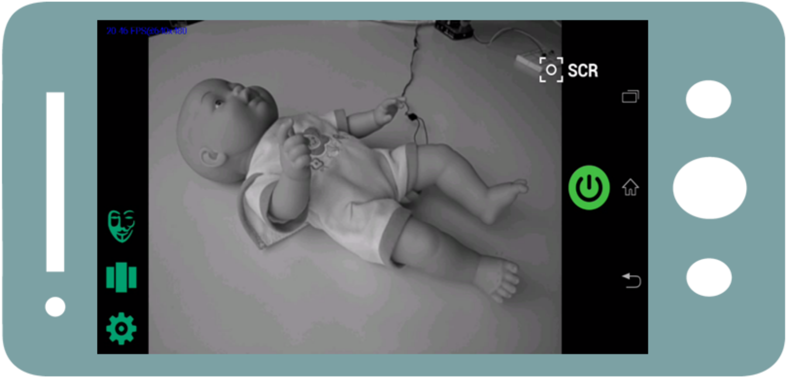
Outline

#smartCED

Smartphone Based Contactless Epilepsy Detector

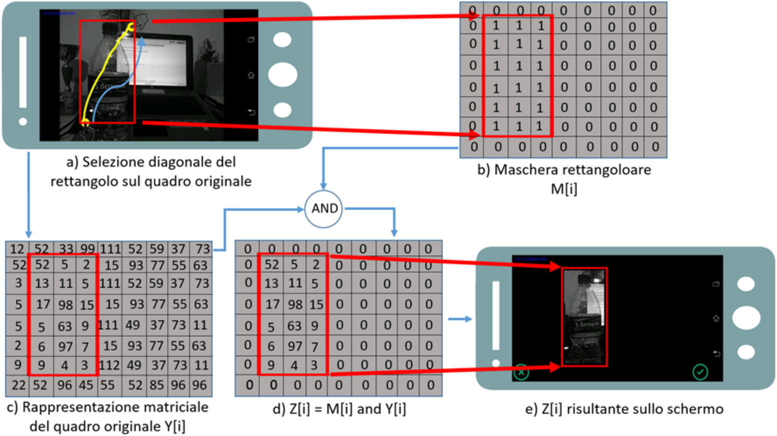
Android application for neonatal seizures detection

SmartCED app



Laboratory test with seizure simulator.

UNIVERSITÀ DI PARMA



b) Maschera rettangoloare M[i]

0	0	0	0	0	0	0	0	0
0	1	1	1	0	0	0	0	0
0	1	1	1	0	0	0	0	0
0	1	1	1	0	0	0	0	0
0	1	1	1	0	0	0	0	0
0	1	1	1	0	0	0	0	0
0	1	1	1	0	0	0	0	0
0	0	0	0	0	0	0	0	0

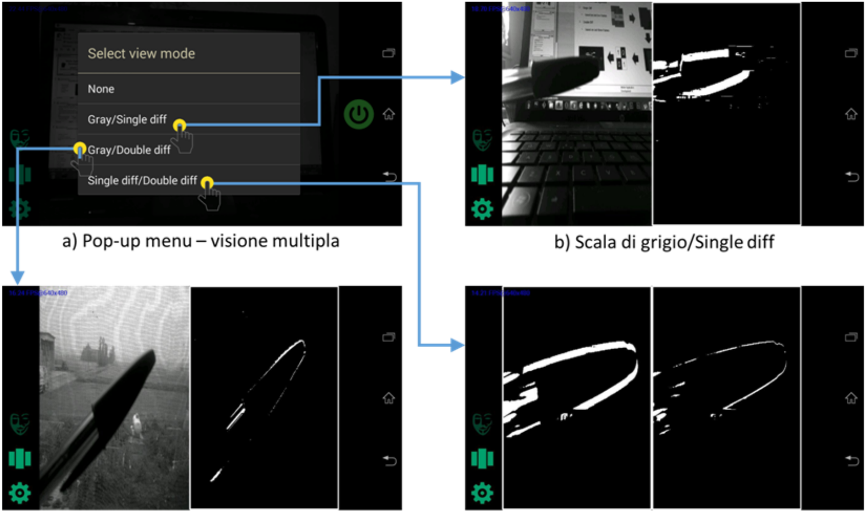
c) Rappresentazione matriciale del quadro originale Y[i]

12	52	33	99	111	52	59	37	73
52	52	5	2	15	93	77	55	63
3	13	11	5	111	52	59	37	73
5	17	98	15	15	93	77	55	63
5	5	63	9	111	49	37	73	11
2	6	97	7	15	93	77	55	63
9	9	4	3	112	49	37	73	11
22	52	96	45	55	52	85	96	96

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

0	0	0	0	0	0	0	0	0
0	52	5	2	0	0	0	0	0
0	13	11	5	0	0	0	0	0
0	17	98	15	0	0	0	0	0
0	5	63	9	0	0	0	0	0
0	6	97	7	0	0	0	0	0
0	9	4	3	0	0	0	0	0
0	0	0	0	0	0	0	0	0

SmartCED app: multiple sights



a) Pop-up menu – visione multipla

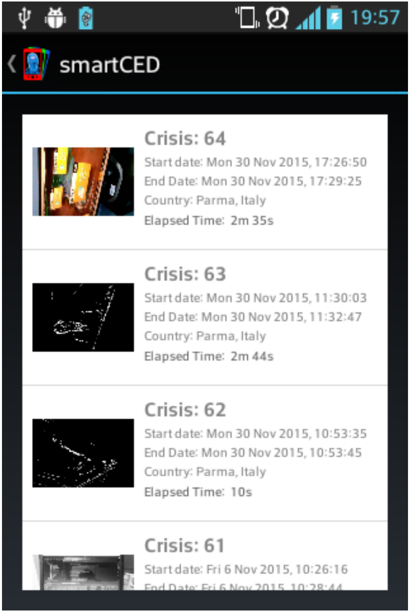
b) Scala di grigio/Single diff

c) Scala di grigio/Double diff

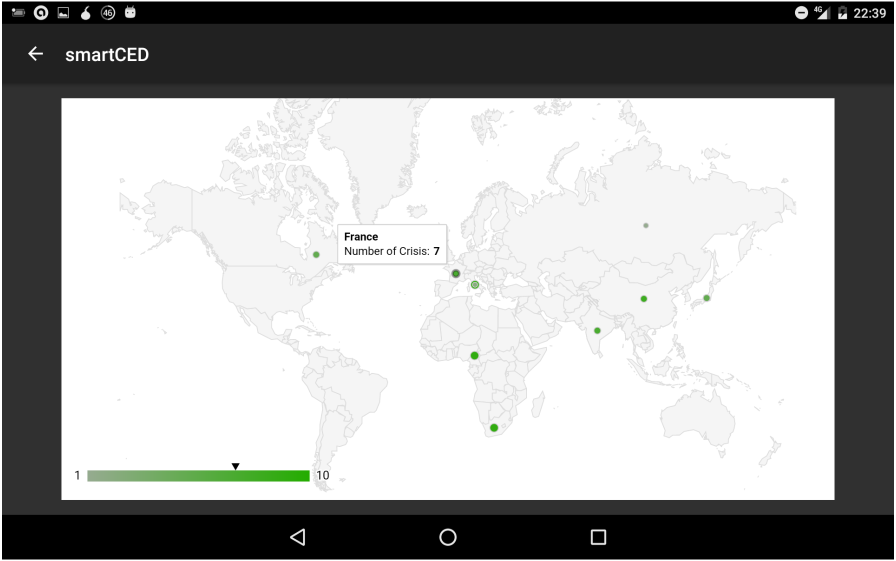
d) Single diff/Double diff

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



Outline

UNIVERSITÀ DI PARMA

Conclusions

UNIVERSITÀ DI PARMA

- 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

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

International Journals

- D. Alinovi, G. Ferrari, F. Pisani, and R. Raheli, “Markov chain modeling and simulation of breathing patterns,” in *Biomedical Signal Processing and Control*, Elsevier, vol. 33, pp. 245–254, March 2017.
- L. Cattani, D. Alinovi, G. Ferrari, R. Raheli, E. Pavlidis, C. Spagnoli, and F. Pisani, “Monitoring infants by automatic video processing: A unified approach to motion analysis,” in *Computers in Biology and Medicine*, Elsevier, vol. 80, pp. 158–165, Jan. 2017.
- E. Pavlidis, G. Cantalupo, L. Cattani, C. A. Tassinari and F. Pisani, “Neonatal seizure automatism and human inborn pattern of quadrupedal locomotion,” in *Gait and Posture*, Elsevier, vol. 49, pp. 232–234, Sept. 2016.
- F. Pisani, E. Pavlidis, L. Cattani, G. Ferrari, R. Raheli and C. Spagnoli, “Optimizing detection rate and characterization of subtle paroxysmal abnormal facial movements with multi-camera video-EEG recordings,” in *Neuropediatrics*, Georg Thieme Verlag, vol. 41, no. 3, pp. 169–174, June 2016.
- F. Pisani, C. Spagnoli, E. Pavlidis, C. Facini, G. M. Kouamou Ntonfo, G. Ferrari and R. Raheli, “Real-time automated detection of clonic seizures in newborns,” in *Clinical Neurophysiology*, Elsevier, vol. 125, no. 8, pp. 1533–1540, Aug. 2014.
- G. M. Kouamou Ntonfo, G. Ferrari, R. Raheli and F. Pisani, “Low-complexity image processing for real-time detection of neonatal clonic seizures,” in *IEEE Transactions on Information Technology in Biomedicine*, vol. 13, no. 3, pp. 375–382, May 2012.

International Conferences

- D. Alinovi, G. Ferrari, F. Pisani, and R. Raheli, "Respiratory rate monitoring by maximum likelihood video processing," in *Proceedings of 2016 IEEE International Symposium on Signal Processing and Information Technology* (ISSPIT), (Limassol, Cyprus), IEEE, Dec. 2016.
- L. Cattani, H. Parmjit Saini, G. Ferrari, F. Pisani and R. Raheli, "SmartCED: an Android application for neonatal seizures detection," in *Proceedings of 2016 IEEE International Symposium on Medical Measurements and Applications* (MeMeA), (Benevento, Italy), IEEE, May 2016.
- D. Alinovi, L. Cattani, G. Ferrari, F. Pisani, and R. Raheli, "Video simulation of apnoea episodes," in *Proceedings of 2015 IEEE International Conference on Multimedia and Expo Workshops* (ICMEW), (Turin, Italy), IEEE, June 2015.
- D. Alinovi, L. Cattani, G. Ferrari, F. Pisani, and R. Raheli, "Spatio-temporal video processing for respiratory rate estimation," in *Proceedings of 2015 IEEE International Symposium on Medical Measurements and Applications* (MeMeA), (Turin, Italy), IEEE, May 2015.
- L. Cattani, D. Alinovi, G. Ferrari, R. Raheli, E. Pavlidis, C. Spagnoli, and F. Pisani, "A wire-free, non-invasive, low-cost video processing-based approach to neonatal apnoea detection," in *Proceedings of 2014 IEEE Workshop on Biometric Measurements and Systems for Security and Medical Applications* (BIOMS), (Rome, Italy), IEEE, Oct. 2014.
- L. Cattani, G. M. Kouamou Ntonfo, F. Lofino, G. Ferrari, R. Raheli and F. Pisani, "Maximum-likelihood detection of neonatal clonic seizures by video image processing," in *Proceedings of 2014 8^{th} International Symposium on Medical Information and Communication Technology* (ISMICT), (Florence, Italy), IEEE, Apr. 2014.
- G. M. Kouamou Ntonfo, F. Lofino, G. Ferrari, R. Raheli and F. Pisani, "Video processing-based detection of neonatal seizures by trajectory features clustering," in *Proceedings of 2012 IEEE International Conference on Communications* (ICC), (Ottawa, Canada), IEEE, June 2012.
- G. M. Kouamou Ntonfo, G. Ferrari, F. Lofino, R. Raheli and F. Pisani, "Extraction of video features for real-time detection of neonatal seizures," in *Proceedings of 2011 IEEE International Symposium on a World of Wireless, Mobile and Multimedia Networks* (WoWMoM), (Lucca, Italy), IEEE, June 2011.
- G. Ferrari, G. M. Kouamou Ntonfo, C. Copioli, R. Raheli and F. Pisani, "Low-complexity image processing for real-time detection of neonatal clonic seizures," in *Proceedings of 2010 3^{rd} International Symposium on Applied Sciences in Biomedical and Communication Technologies* (ISABEL), (Rome, Italy), IEEE, Nov. 2010.

Multimedia material

- Video multimedia support for the article "Markov chain modeling and simulation of breathing patterns," in *Biomedical Signal Processing and Control*.
  DOI: `10.1016/j.bspc.2016.12.002`. Direct link.
- Video multimedia support for the article "Monitoring infants by automatic video processing: A unified approach to motion analysis," in *Computers in Biology and Medicine*.
  DOI: `10.1016/j.compbiomed.2016.11.010`. Direct link.

Thank you for your attention!

ANY QUESTION?

The 9th International Conferences on Advances in Multimedia
MMEDIA 2017

MULTIMEDIA Lab

UNIVERSITÀ DI PARMA
DEPARTMENT OF ENGINEERING AND ARCHITECTURE
DEPARTMENT OF MEDICINE AND SURGERY