INDEPENDENT COMPONENTS ANALYSIS FOR FETAL ELECTROCARDIOGRAM EXTRACTION: A CASE FOR THE DATA EFFICIENT MERMAID ALGORITHM

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Introduction

- Despite its limitations, fetal heart rate (FHR) tracing analysis is our best monitor of fetal well-being during labor. Transabdominal ultrasound has limitations: tracing loss during fetal movement, potential to confuse maternal for fetal heart rate, inability to monitor during cesarean delivery or abdominal surgery.The alternative, fetal scalp electrode monitoring, has risks including infection and hematoma.
- FECG extraction is a well-known problem of mixed signals – the FECG is hopelessly contaminated by the maternal ECG, maternal electromyograph (EMG), and noise. Hence, in order to be monitored, the FECG has to be separated from these noisy elements. Numerous methods have been used to solve this extraction problem in particular the well-established blind source separation techniques.
- The MERMAID algorithm was first tested on synthetically mixed data and then embedded into data collection software that interfaced with custom ECG hardware and standard maternal-fetal monitors (Corometrics).

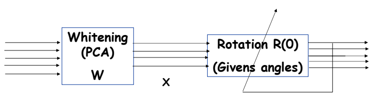
MERMAID algorithm for ICA

- *Contrast function:* Renyi's mutual information and Kullback-Leibler divergence.

(1) $J=\sum_{o=1}^{n} H_\alpha(y^o)$

where $H_\alpha(y^o)$ is the marginal order-α Renyi's entropy for the random variable y^o of the output channel o, and n is the dimensionality of the output vector Y.

- *Optimization algorithm:* Gradient descent.



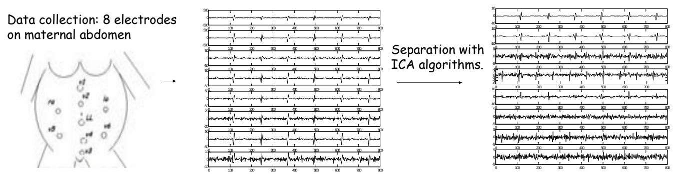
The Mermaid algorithm determines the separated sources using the following steps:

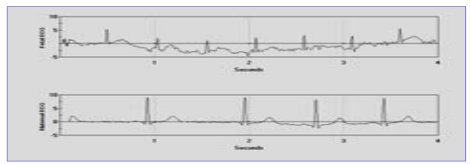
1. Initialize the Givens angles (to all zeros or randomly).
2. Compute the whitening matrix as prescribed using all samples in off-line separation or update the whitening matrix using an adaptive PCA algorithm in on-line separation.
3. In off-line separation, use the batch gradient, which is computed using all available samples. In on-line separation, use the stochastic gradient in (2), which uses only L samples, including the most recent sample at time k.

(2) $$\frac{\partial J}{\partial \theta_{kl}} = -\sum_{o=1}^{n} \frac{\sum_{j=1}^{N}\left(\sum_{i=1}^{N}\kappa_\sigma(y_j^o - y_i^o)\right)^{\alpha-2}\left(\sum_{i=1}^{N}\kappa'_\sigma(y_j^o - y_i^o)\left(\frac{\partial y_j^o}{\partial\theta_{kl}} - \frac{\partial y_i^o}{\partial\theta_{kl}}\right)\right)}{\sum_{j=1}^{N}\left(\sum_{i=1}^{N}\kappa_\sigma(y_j^o - y_i^o)\right)^{\alpha-1}}$$

4. Update the Givens rotation angles using steepest descent. $\Theta = \Theta - \eta \dfrac{\partial J}{\partial \Theta}$

Results on real ECG mixtures





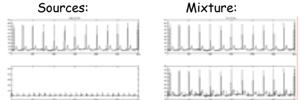
Post processing algorithms: Maternal and fetal channel selection and waveforms reconstruction

Tables: Comparison with the different algorithms in terms of trust factor.

Data Set	*Mermaid-SIG*	*Infomax*	*FastICA*
Average Trust	4.4	2.8	3.3

Results on artificially mixed signals

Comparison on a mixture of artificially made fetal, maternal ECG signals and noise:



- Effect of entropy order and kernel size on the performance of Mermaid.

Result: for optimal performance fix the order to 2 and the kernel size to 0.25.

Table: Results on artificially mixed data. Comparison with other ICA algorithms.

Algorithm	# samples	SDR max (dB)	# of iterations
Noisy Artificial Data			
Mermaid-SIG	100	50	20
Infomax	100	25	80
Fast ICA	500	20	batch
Varying Mixing Matrix			
Mermaid-SIG	100	30	50
Infomax	100	7	80
Fast ICA	500	22	batch

Measures of performance

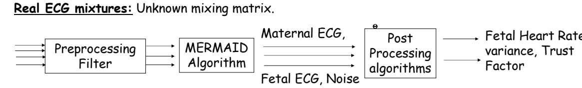
- **Artificial Mixtures:** known mixing matrix, H.

Signal to distortion ratio: measures the closeness of the product of the mixing and separation matrices to a perfect separation scenario .

$$SDR=\frac{1}{n}\sum_{i=1}^{n}10\log_{10}\left(\frac{(\max_j O_{ij})^2}{\sum_{j=1}^{n}O_{ij}^2-(\max_j O_{ij})^2}\right)$$ Where O=RWH.

A larger SDR signifies a better separation of the original sources, thus means a better performance of the separation algorithm used.

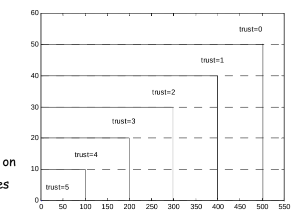
Real ECG mixtures: Unknown mixing matrix.



Post Processing algorithms:

- Modified Pan Tompkins QRS detection algorithm.
- Heart rate and Heart rate variance calculation.
- Maternal and fetal channel selection.
- Trust Factor computation, based on HR, HR variance, False Positive and Negative.

Trust Factor: separation reliability factor , based on intrinsic properties of the FECG and FHR, quantifies the separation success from 0 (no separation) to 5.



CONCLUSION

- The experimental results in artificially mixed ECG signals and fetal heart rate detection from real ECG measurements showed that Mermaid outperforms the 2 other ICA algorithms tested: FastICA and Infomax. Mermaid is shown to be more data efficient both in batch and on-line operation modes, which is an important feature for real-time implementation, since the mixture model could be time-varying in real mixtures.

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