Real-Time Fetal Heart Monitoring in Biomagnetic Measurements Using Adaptive Real-Time ICA

Stephan Waldert*, Michael Bensch, Martin Bogdan, Wolfgang Rosenstiel, *Member, IEEE*, Bernhard Schölkopf, Curtis L. Lowery, Hari Eswaran, and Hubert Preissl

***Abstract*—Electrophysiological signals of the developing fetal brain and heart can be investigated by fetal magnetoencephalography (fMEG). During such investigations, the fetal heart activity and that of the mother should be monitored continuously to provide an important indication of current well-being. Due to physical constraints of an fMEG system, it is not possible to use clinically established heart monitors for this purpose. Considering this constraint, we developed a real-time heart monitoring system for biomagnetic measurements and showed its reliability and applicability in research and for clinical examinations. The developed system consists of real-time access to fMEG data, an algorithm based on Independent Component Analysis (ICA), and a graphical user interface (GUI). The algorithm extracts the current fetal and maternal heart signal from a noisy and artifact-contaminated data stream in real-time and is able to adapt automatically to continuously varying environmental parameters. This algorithm has been named Adaptive Real-time ICA (ARICA) and is applicable to real-time artifact removal as well as to related blind signal separation problems.**

***Index Terms*—Adaptive, clustering, fetal, independent component analysis, magnetoencephalography, real-time systems.**

I. Introduction

FETAL magnetoencephalography (fMEG) is a completely noninvasive, passive, and innocuous method enabling investigations on fetal brain activity in utero. In order to perform fMEG investigations on healthy fetuses and fetuses at risk, the fetal well-being should be monitored continuously in real-time. Certain aspects of fetal well-being can be quantified by the fetal heart signal [1]. Furthermore, maternal well-being affects the fetus [2]. Therefore, the maternal heart signal should be monitored as well. Both the maternal and the fetal heart signals are contained in the fMEG; they are referred to as magnetocardiography (MCG). There are clinically established heart monitoring systems but they cannot be applied during biomagnetic measurements. Consisting of metallic and electronic components, these devices would interfere with the fMEG signal. Hence, there is a need to establish ways to enable fetal and, simultaneously, maternal heart monitoring during fMEG investigations.

Manuscript received July 24, 2006. This study was supported by the NIH grant 1R01NS3677-04A1, the WIN-Kolleg of the Heidelberg Academy of Sciences and Humanities, and the DFG 1030 Ro/12-1. *Asterisk indicates corresponding author.*

*S. Waldert is with the MEG-Center, University of Tübingen, 72076 Tübingen, Germany (e-mail: stephan.waldert@med.uni-tuebingen.de).

M. Bensch and W. Rosenstiel are with the Department of Computer Engineering, University of Tübingen, 72076 Tübingen, Germany.

M. Bogdan is with the Department of Computer Engineering, University of Tübingen, 72076 Tübingen, Germany. He is also with the Department of Computer Engineering, University of Leipzig, 04109 Leipzig, Germany.

B. Schölkopf is with the Max Planck Institute for Biological Cybernetics, 72076 Tübingen, Germany.

C. L. Lowery and H. Eswaran are with the Department of Obstetrics and Gynecology, University of Arkansas for Medical Sciences, Little Rock, AR 72205 USA.

H. Preissl is with the MEG-Center, University of Tübingen, 72076 Tübingen, Germany. He is also with the Department of Obstetrics and Gynecology, University of Arkansas for Medical Sciences, Little Rock, AR 72205 USA.

Digital Object Identifier 10.1109/TBME.2007.895749

(a) (b)

Fig. 1. (a) 151-channel SQUID fMEG system SARA. (b) Photograph showing the positioning of a pregnant woman during an fMEG recording.

The most obvious approach is an analysis of the data provided by an fMEG system; we will use the term “biomagnetic data” to refer to these data, which always contain both encephalic (fMEG) and cardiac (MCG) signals. The aim of analyzing the biomagnetic data is to extract the fetal and maternal heart signal in real-time from a data stream containing both signals as well as noise and artifacts. Thereby, continuously varying environmental parameters, such as maternal breathing or varying position and orientation of the fetus due to movements, must be compensated for automatically.

Several methods exist that extract the fetal heart signal from data obtained by fetal magneto- or electrocardiography [3]–[8]. Furthermore, analyses can be performed by Independent Component Analysis (ICA) [9]–[13]. To our knowledge, none of these methods has been used for real-time heart monitoring; for some methods it would be impossible due to their computational burden. Thus, our goal was first to develop a new approach that enables real-time application of ICA, and second, based on this approach, to create a system that enables real-time heart monitoring in fMEG.

II. Materials and Methods

A. fMEG System

Measurements were performed with the SQUID fMEG system SARA (VSM MedTech Ltd., Fig. 1) [14]. The system is installed in an electromagnetically shielded room. The mother sits and leans her abdomen against an anatomically shaped sensing surface, which contains an array of 151 SQUID sensors and covers the mother’s anterior abdominal surface from the perineum to the top of the uterus.

B. Test Environment

The real-time heart rate monitoring system was tested on the following system: Intel Xeon 2.8 GHz dual processor, 512 kB Cache, 2 GB RAM. The following software was used for creation and tests of the real-time heart monitoring system: Linux 2.4.18-26.7.xsmp, Red Hat Linux 7.3 2.96-112, gcc 2.96, Matlab V6.5.1.199709 R13 SP1, FastICA 2.4, RealTime 1/21/2004, Acq 4.18.

C. Dataset

Sixteen datasets of 15 pregnant subjects were recorded with the SARA system. The study was approved by the local Institutional Review Board. Each subject signed an informed consent. Gestational age was between 27 and 39 weeks. A sample rate of 312.5 Hz and 151 channels were used for recording. The strength of fetal movements (ranging from no movements to strong movements) was judged by the mother and ultrasonic measurements before and after the investigation.

Method II-D is included for performance comparison to the new system, which incorporates Methods II-Eto II-I.

D. Initial Algorithm (Only for Comparison)

Our initial heart rate extraction algorithms, the first published in [15] and the second (described below) an extension of the former, were designed to calculate heart rates based on analyses of a signal's energy. These two algorithms are real-time compatible and allow the detection of fetal and maternal R-peaks; however, false detections occur during analysis.

The major steps of this energy based algorithm can be described as follows: Based on channel positions, the signals recorded by a fixed set of channels are designated as fetal or maternal. After high-pass filtering (Butterworth, fourth order, 10 Hz), the maternal and fetal R-peaks, $R_m(n)$ and $R_f(n)$, respectively, are detected. This is accomplished by threshold detection with the thresholds $\theta_m = 3.5 \cdot STD(g_m)$ and $\theta_f = 2.7 \cdot STD(g_f)$; where g_m and g_f is the mean signal of the corresponding signal group and STD the standard deviation. The factors were chosen based on heuristics. Due to false detections occurring in $R_m(n)$ and $R_f(n)$, a heuristic method is applied for correction. A periodic signal is reconstructed by removing unreasonable peak detections and completing missing ones, whereas the influence of detected peaks on the time point of interest decreases with temporal distance. This method is balanced in the sense that it tries to maintain a stable heart rate while still being flexible enough to keep track of heart rate variations. For the remainder of this paper, the term "algorithm EB" (energy based) refers to this algorithm plus heuristic.

E. Real-Time Access to fMEG Data

In typical MEG investigations, biomagnetic data are acquired and saved by a control program. Afterwards, these data can be analyzed off-line. For real-time data access, as required for the real-time heart monitoring system, a support program (RealTime, VSM MedTech Ltd.) creates a shared memory segment in memory. Thereby, the control program collects and subsequently writes biomagnetic data (in the form of packets) into the shared memory segment during recordings. The support program constantly checks for packets within the storage. If a packet is present, it will be read by the support program. We modified the support program (written in C/C++) in order to make biomagnetic data accessible to other applications. Due to our modifications, we are able to arbitrarily address each sensor and data value.

The real-time heart monitoring system was developed using Matlab (MathWorks Inc., MA, USA). We created an interface with C/C++, which enables bidirectional communication between C/C++ (the real-time access) and Matlab, by utilizing the functions of the header file "engine.h" and so called "MEX-files". This interface can be used for other on-line applications as well. For our purpose, the interface completely controls the data transfer between the real-time access and the real-time heart monitoring system.

However, the mode of operation of the protected software delivered with the fMEG system (mainly the packet-wise data transfer) creates an artificial delay between signal occurrence and accessibility. Thus, a maximum delay of 100 ms can be reached for sample rates of 625 Hz and upwards, 200 ms for 312.5 Hz [16].

F. Independent Component Analysis

Data provided by an fMEG system are mixtures of signals emitted by multiple (independent) sources. These sources are mainly the maternal and fetal heart, the fetal brain, movements or muscle activity of the mother and fetus, and noise. ICA [17] allows the extraction of the fetal and maternal heart signals from this mixture and can be described as follows:

If $s_i,\ i \in [1,m]$, are the signals emitted by m independent sources s, and n is the number of sensors simultaneously recording these signals over time t, the recorded data $x_j,\ j \in [1,n]$, of each sensor contain signals originating from more than one source, i.e., each sensor records a mixture of the sources. Assuming a linear, time-invariant, and memoryless mixing, this can be formulated as

$$\boldsymbol{x} = A \cdot \boldsymbol{s} \tag{1}$$

where A is called the mixing matrix and $\boldsymbol{x} = [x_1; \ldots; x_n]$ and $\boldsymbol{s} = [s_1; \ldots; s_m]$.

In order to recover the original source signals s_i, the mixture must be inverted. Consequently, each ICA method estimates the mixing matrix A with respect to $\boldsymbol{x}$ and provides a set of independent components. These components (y_i) ultimately constitute estimates of s_i. It should be noted that ICA provides no scaling information about s_i. This means that successive scaling does not constitute an additional constraint for further processing. Based on [9], [12], [18]–[20], we selected FastICA [21], [22] for the heart signal extraction. It is based on a fixed-point iteration scheme and utilizes maximization of non-Gaussianity measured by kurtosis or approximated negentropy. Generating maximum non-Gaussian components is equivalent to generating maximum independent components, as stated by the central limit theorem. By default, FastICA starts with a randomly initialized mixing matrix A but especially the possibility of initializing FastICA with a predefined mixing matrix A^* constitutes the basis of our Adaptive Real-time ICA (ARICA). If A^* is used for initialization, certain components can be selected in advance and convergence can be significantly accelerated.

G. Noise Level

In order to select the clearest fetal and maternal component, the noise level of each extracted component must be determined. Therefore, each component y_i is scaled so that the maximum absolute value equals 1. Afterwards, the R-peaks and other high amplitude heart signals, such as S- and T-peaks, are removed by threshold detection (amplitudes larger than two times the standard deviation are set to 0), resulting in y_i^p. With n being the number of samples of y_i, the sum of point-wise distances between the component and its low-pass filtered (LP) counterpart (Butterworth, fourth order, 6.25 Hz) then reflects the noise level:

$$\text{NoiseLevel}(y_i) = \sum_{t=1}^{n} \left| y_i^p(t) - LP\left(y_i^p(t)\right) \right| \quad \forall i. \tag{2}$$

H. Clustering

One problem of ICA is that a single source may project to several components, i.e., several extracted components reflect the signal of one source. These similar components can be grouped for further processing by clustering. Thereby, the degree of similarity is computed by a distance function. A possible distance function is mutual information (MI) [23], which measures the level of dependence and also covers nonlinear relations (higher order statistics) between the components. The distance between two components is calculated by pair-wise MI as follows: $MI(X,Y) = H(X) + H(Y) - H(X,Y)$; where $H(X)$ and $H(Y)$ are the entropies of X and Y; and $H(X,Y)$ is the joint entropy of X and Y. Estimators for multivariate (higher order) MI were taken into consideration [24]. However, their computational burden was too high and clustering using pair-wise MI fulfilled requirements. After computing the n-over-2 pair-wise MI values (n being the number of components), clustering is performed using the Matlab functions “linkage” and “cluster”.

I. Wavelet Denoising

The signal-to-noise ratio of the extracted components can be improved by wavelet denoising [10]. Wavelet denoising is based on wavelet transformation, which can be applied to transform a signal from time domain into wavelet domain [25], i.e., wavelet coefficients. Thereby, large coefficients reflect main features of the signal, whereas details are reflected in small coefficients. The noise in the original signal is removed by omitting small coefficients before applying an inverse wavelet transformation. Thus, the process of wavelet denoising is described as follows:

1) wavelet transformation $\rightarrow$ wavelet coefficients;
2) thresholding (coefficients with an absolute value less than the threshold are set to 0);
3) inverse wavelet transformation $\rightarrow$ denoised signal.

We selected the Daubechies wavelet of length 8.[1] We used this approach to denoise the fetal and maternal signals extracted by FastICA. The threshold was heuristically determined and set to 3.

[1]A corresponding software package is available at http://nt.eit.uni-kl.de/wavelet/download.html free of charge.

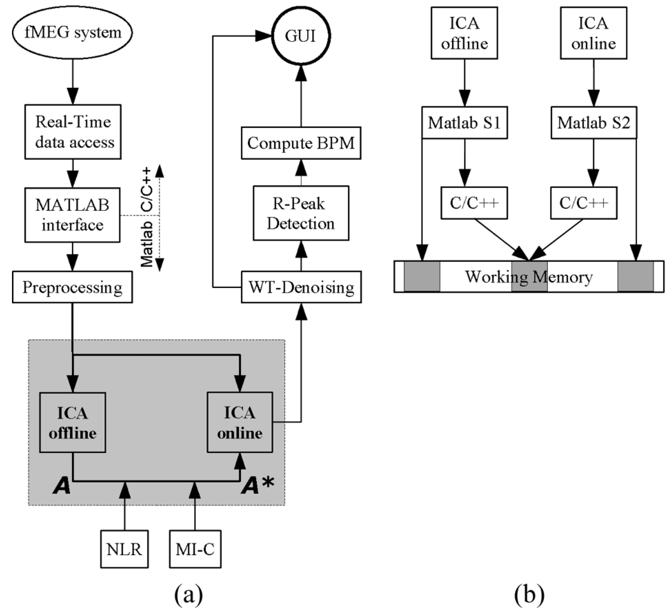

Fig. 2. (a) Flowchart showing main parts of data flow of the real-time heart monitoring system (NLR: Noise Level Ranking; MI-C: Mutual Information Clustering; BPM: Beats Per Minute; GUI: Graphical User Interface; WT: Wavelet Transformation). The gray rectangle depicts ARICA. (b) Computational realization of data transfer and communication within ARICA. The left and right gray areas represent working space of Matlab session 1 (S1) and Matlab session 2 (S2); the middle gray area represents a shared memory segment.

III. Implementation

The flowchart of Fig. 2(a) depicts the data flow and main parts of the real-time heart monitoring system. Our approach realizing ARICA is marked by a gray rectangle; details of implementation are shown in Fig. 2(b). The following steps describe the different parts of the system.

1) The fetal and maternal heart and muscle activity, fetal brain activity, and noise are recorded by the fMEG system.

2) The real-time access provides these data to a C/C++ –Matlab interface; from this point on the data are analyzed in Matlab.

3) The preprocessing starts with the fixed selection of 16 sensors distributed uniformly over the sensor array. This selection covers the whole abdomen (independence of fetus’s position) and provides an amount of data which is sufficient to analyze heart activity and processable in real-time.

4) The signals of these 16 sensors are high-pass filtered (Butterworth, fourth order, 1.5 Hz) in order to remove possible offset, trend, and low-frequency artifacts originating from breathing, for instance.

5) The preprocessed signals are then provided to ARICA. As can be seen in the flowchart in Fig. 2(a), ARICA consists of two identical ICA algorithms, ICAoffline and ICAonline, which run in parallel and analyze the biomagnetic data. Both algorithms are able to interact using shared memory [Fig. 2(b)].

5a) At the beginning, ICAoffline evaluates the filtered signals and estimates a mixing matrix A (representing 10 components), which enables a separation of the mixed signals into several components.

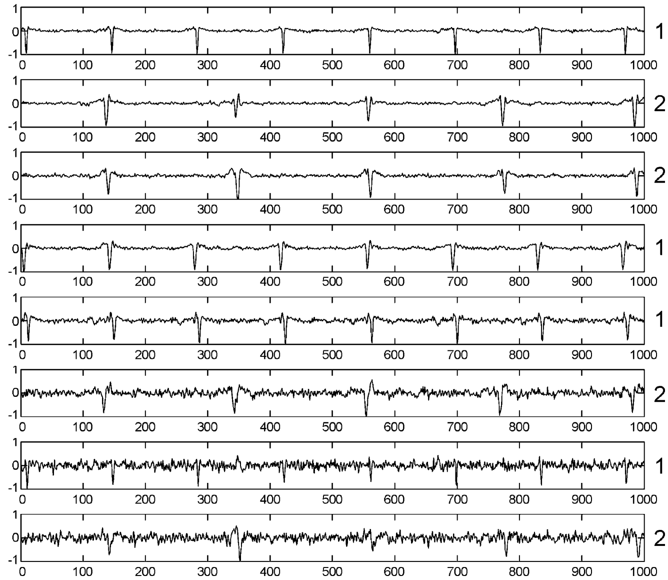

Fig. 3. Eight components extracted by ICAoffline, scaled and ranked according to their noise level (Noise Level Ranking). The numbers on the right side indicate the cluster assignment by MI-Clustering (1-fetal, 2-maternal, abscissa reflects sample number, ordinate reflects scaled output, sample rate is 312.5 Hz). The upper graph of Fig. 5 represents the raw biomagnetic signal (of one channel) underlying these components.

5b) These components are ranked according to their noise level (lowest noise level first).

5c) After Noise Level Ranking, the components are clustered into two groups using MI-Clustering. As a result, the clearest fetal and maternal component is now at the top of its corresponding group.

The last two steps are visualized in Fig. 3; it can be seen that all maternal and all fetal components are separately grouped.

5d) The maternal group is identified by possessing a higher correlation between its top component and the signal of a sensor recording mainly maternal heart activity, i.e., the sensor closest to the mother's heart.

5e) The clearest fetal and maternal component can be traced back to the mixing matrix A, which is reduced accordingly to A^*. A^* now reflects only the clearest fetal and maternal signal possible based on the provided data.

5f) After this step, ICAonline is called to evaluate current biomagnetic data. ICAonline, initialized with A^*, slightly adapts A^* (i.e., refines the entries of A^* according to the current data in order to provide the best possible separation) and computes the current fetal and maternal heart signal, which are displayed in the GUI. Now, ICAonline is continuously called every time a certain number (1 to 32 or more) of new samples per sensor is available.

5g) Meanwhile, the interface constantly checks if ICAoffline has completed previous calculations and is ready to estimate a new mixing matrix A. If that is the case, it supplies new data to ICAoffline (goto 5a). The resulting (reduced) new mixing matrix A^* is again used as initialization in ICAonline (goto 5f). For details of temporal relations see Fig. 4.

6) As one of the last steps, Wavelet Denoising is applied to the output of ICAonline, i.e., to the extracted fetal and maternal heart signal.

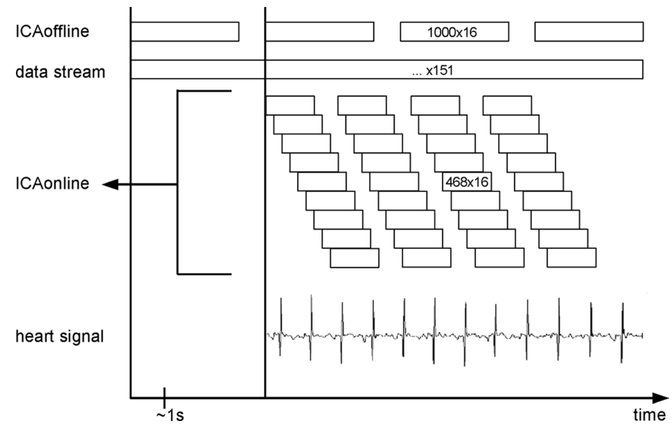

Fig. 4. Temporal relations between ICAonline and ICAoffline. The boxes represent biomagnetic data processed by ICAonline and ICAoffline at a particular time. The spaces between the ICAoffline boxes indicate the time required to process data, estimate the mixing matrix A, and to create A^*.

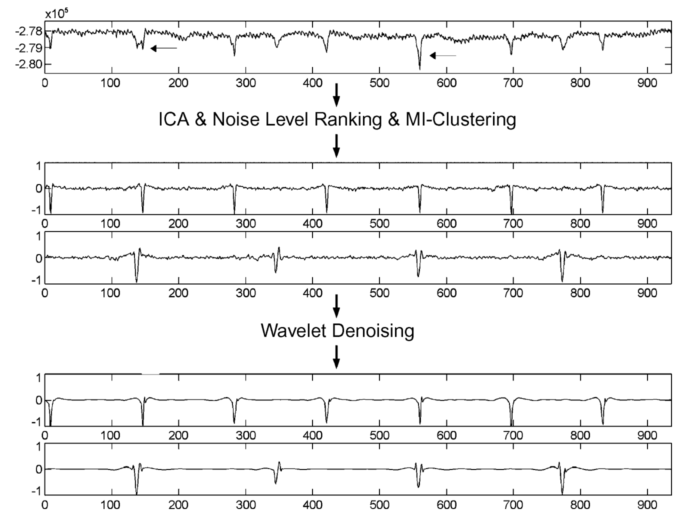

Fig. 5. Input and output of the real-time heart monitoring system. Abscissa shows sample number, sample rate is 312.5 Hz. The top graph shows a typical biomagnetic signal (recorded with fMEG) containing fetal brain activity, noise and maternal and fetal heart activity (ordinate reflects magnetic field strength with offset in Tesla). Overlapping maternal and fetal heart beats are indicated by arrows. The middle graph shows a fetal and maternal component extracted by ARICA. The lower graph shows the same components after Wavelet Denoising. The heart rates and these heart curves are presented in the GUI.

7) The denoised signals are displayed in the GUI.

8) R-peaks are detected by threshold detection. The instantaneous heart rate is calculated based on pair-wise temporal spacing between R-peaks and, subsequently, displayed in the GUI.

IV. Results

The main stages of data processing are summarized in Fig. 5. The upper graph shows a raw biomagnetic signal recorded by one sensor of the fMEG system. The middle graph visualizes the result of applying FastICA (initialized with mixing matrix A^*), Noise Level Ranking, and MI-Clustering, i.e., the modules of ARICA, to the presented and the remaining 15 simultaneously recorded, raw biomagnetic signals. The bottom graph is obtained after wavelet denoising; the heart rates are computed based on these extracted signals.

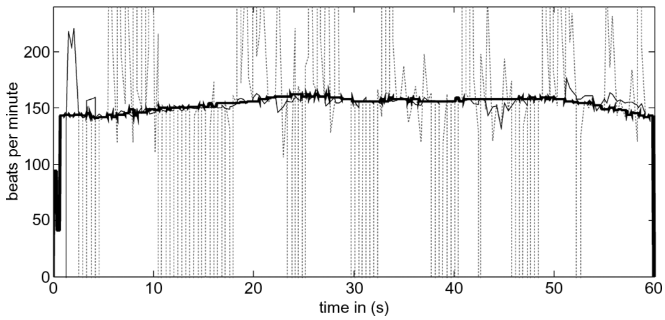

Fig. 6. Fetal heart rate computed by the algorithm EB with (thin, solid line) and without (dashed line) heuristic and the real-time heart monitoring system (bold line). It is important to note that only the graph of the algorithm EB without heuristic and of the real-time heart monitoring system reflects the instantaneous heart rate.

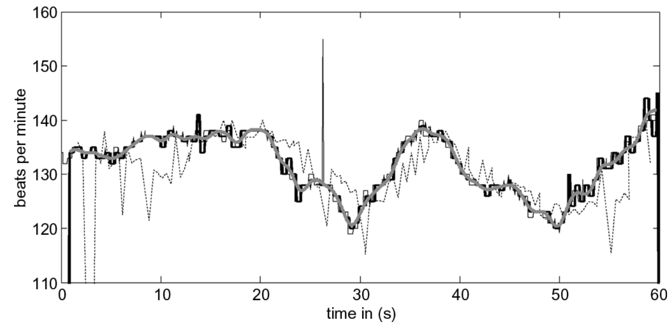

Fig. 7. Fetal heart rate computed by the algorithm EB (dashed line), the real-time heart monitoring system (bold line), and the approach in which A^* is calculated only once at the beginning and is not regularly updated (thin, solid line). The bold line and the thin, solid line are almost identical, whereas the dashed line shows variation from the others and the thin, solid line shows an outlier. Furthermore, the low-pass filtered output of the real-time heart monitoring system is shown (gray line). The heart rate extracted by the algorithm EB without heuristic is omitted for the sake of clarity.

Sixteen recordings of 15 pregnant subjects were analyzed. Test results are described by the example visualized in Fig. 6. The extracted heart rate is shown for the algorithm EB without heuristic (dashed line), the algorithm EB (thin, solid line), and the real-time heart monitoring system utilizing ARICA (bold line). The borders (first and last second) should not be considered; they result solely from test setup. Only the fetal heart rate is shown; the maternal heart signal is much stronger and can be evaluated easily. To provide an overall quality measure, the extracted heart rates were validated by off-line detection of maternal and fetal heart signals: A template matching algorithm followed by orthogonal projection was used to attenuate the detected signal. This procedure is used on a regular basis to attenuate the maternal and fetal MCG in fMEG recordings and, therefore, allows the detection of maternal and fetal heart beats [26]. False or missed detections were corrected by hand after visual inspection to obtain an absolute correct reference for all 16 datasets $(h1)$. Possible outliers in the heart rates extracted by the real-time heart monitoring system were excluded by hand in advance $(h2)$, i.e., 98.61% of all data points were used. The correlation coefficient (r) of $h1$ and $h2$ was computed: $median(r) = 0.96$, $first\ quartile(r) = 0.92$, $third\ quartile(r) = 0.98$; for each dataset r was highly significant $(p < 0.001)$.

As can be seen in Fig. 6, the algorithm EB without heuristic fails to detect several heart beats or detects too many, the algorithm EB (with heuristic) can balance (but is clearly affected by) these false detections, and the real-time heart monitoring system utilizing ARICA provides a stable performance. It is important to recall that the algorithm EB uses a heuristic, i.e., the presented heart rate graph does not reflect the instantaneous heart rate; it is rather an optimized, automatic interpretation of the actual heart rate. In contrast, the output of the real-time heart monitoring system does reflect the instantaneous heart rate.

For an application of the real-time heart monitoring system on a single processor system, we tested the effect of initializing ICAonline every time with the same mixing matrix A^*. In this approach, A^* is calculated only once at the beginning and is not regularly updated (according to current data) by a second ICA (ICAoffline) running in parallel. Fig. 7 exemplifies the result of these tests. Compared to the heart rate extracted by ARICA (bold line), the graph of the aforementioned approach shows one outlier (thin, solid line). Similar outliers can be observed in other recordings as well. These results show that the overall performance is better with ARICA. In addition, regular updates of A^* speed up the system (real-time requirements) and allow adaptivity to nonstationary signal sources.

In further tests (not shown), we ensured that the obtained results were not due to a randomly matching beginning of the evaluated datasets. Therefore, the first 1600 samples of each dataset were removed. The real-time heart monitoring system was applied to this shortened dataset, whereas the removal of 1600 samples ensures that the two ICA algorithms process different data windows than they do for the whole dataset.

A delay between heart beat occurrence and its reflection in an updated heart rate and heart signal in the GUI is mainly based on the real-time access (up to 200 ms for a sample rate of 312.5 Hz due to a packet-wise data transfer) and the time needed by ICAonline computations (30 ms to 70 ms, depending on convergence speed). Another contribution to the delay consists of polling for user inputs and refreshing of the GUI (up to 4 ms). The data transfer and communication between both Matlab sessions (ICAonline and ICAoffline) by shared memory constitutes a negligible delay in sub-ms range (<1 ms). In summary, the maximum delay is approximately 374 ms and the minimum is approximately 68 ms, if the heart beat occurs shortly before a packet is transferred and analyzed. In the field of heart monitoring, this range still justifies the use of the term real-time. It should be noted that, despite the varying delay, the sampling process itself preserves the chronological information regarding when a certain signal occurred. Running in parallel and without affecting the delay, ICAoffline performs each calculation within 3 s to 5 s (depending on convergence speed). This means that every 3 s to 5 s new data are analyzed and the mixing matrix A is updated to current data.

V. Discussion and Conclusion

We presented a robust, autonomous heart monitoring system enabling real-time observation of fetal and maternal heart activity in biomagnetic measurements (fMEG). This system is based on ARICA, an Adaptive Real-time ICA. ARICA, in turn, utilizes an automatic selection of the clearest fetal and maternal component. This selection is based on MI-Clustering and the developed Noise Level Ranking.

Being based on ICA, the system even allows separation of completely overlapping or synchronous heart beats (Fig. 5), which is nearly impossible for methods evaluating the signal's energy. The uniform channel distribution makes the system independent of the fetus's position, i.e., no prior knowledge is used. Actually, the only prior knowledge used consists of the choice of a channel containing mainly maternal signals (to identify the maternal cluster). However, this choice does not pose a constraint because the maternal heart is a strong signal source located at a well defined position.

The reliability of the real-time heart monitoring system was verified through analyses of 16 datasets and their modified versions.

The functionality of ARICA was proven by proper functioning of the real-time heart monitoring system. Based on FastICA, the approach of estimating current mixing matrices A in parallel and to transfer the corresponding data by shared memory turned out to be very effective. Even if environmental parameters change, the regular new initializations by A^* ensure that ICAonline can compute the current fetal and maternal signals without interruption in real-time. Applying these regular initializations also ensures that movements of the mother or fetus (the signal sources) are compensated for and possible changes in their well-being during investigations are tracked automatically. Even recordings containing moments of strong maternal or fetal movements were reliably processed.

In general, ICA methods cannot separate signals that are correlated. The question in the context of the real-time heart monitoring system is, whether there is any coupling between the fetal and maternal heart. Van Leeuwen *et al.* [27] found that such (numerical) couplings occur occasionally only.

With regard to ICA generating independent components, clustering these components using MI as distance function seems counterintuitive. The following two points should be considered in this context: ICA methods generate components that are as independent as possible, and MI also covers higher order dependence. However, it rarely occurs that a fetal component slips into a maternal cluster or vice versa. If this incorrectly assigned component additionally contains the lowest noise level, two identical heart signals and rates (both fetal or maternal) are extracted. This malfunction is corrected by the next ICAoffline calculation, which takes about 3 s to 5 s, and indicated in the GUI by a flashing light.

The term "adaptive" in ARICA was chosen for two reasons. First, ARICA can handle nonstationary sources and varying environmental conditions. Second, due to the possibility of increasing the update rate by parameter settings, every new data sample available could be taken into account. If more processors were used, the mixing matrices could be updated more often and the continuously running ICA could work on a data window sliding in real-time sample per sample over the data to be analyzed. Thereby, the advantages of a batch/semi-adaptive ICA method are utilized in an adaptive manner, whereas the usage of learning rules/sequences, which strongly affect results and can even destroy convergence [21], is avoided.

The GUI presents current heart rates and extracted heart curves. General features of the latter could be interpreted by experts to gain further information about fetal and maternal well-being. The peak ratio between and temporal occurrences of the PQRST-curve elements are preserved throughout the whole data processing. An automatic classification of the features by Support Vector Machines or related methods remain future possibilities.

ARICA may be applied for adaptive real-time blind signal separation in several fields. It allows automatic real-time artifact removal or extraction of signals of interest by replacing the peak signal extraction in the current algorithm with appropriate modifications according to the investigated signal characteristic. Thus, ARICA may be utilized to provide clear signals to be further analyzed in real-time, which could also improve brain-machine interface applications.

REFERENCES

[1] J. J. Smith and J. Onstad, "Assessment of the fetus: Intermittent auscultation, electronic fetal heart rate tracing, and fetal pulse oximetry," *Obstetrics and Gynecology Clinics of North America*, vol. 32, no. 2, pp. 245–254, Jun. 2005.

[2] C. Monk, R. Sloan, M. Myers, L. Ellman, E. Werner, J. Jeon, F. Tager, and W. Fifer, "Fetal heart rate reactivity differs by women's psychiatric status: An early marker for developmental risk?," *J. Am. Acad. Child Adolesc. Psychiatry*, vol. 43, no. 3, pp. 283–290, Mar. 2004.

[3] P. Kanjilal, S. Palit, and G. Saha, "Fetal ECG extraction from single-channel maternal ECG using singular value decomposition," *IEEE Trans. Biomed. Eng.*, vol. 44, no. 1, pp. 51–59, Mar. 1997.

[4] A. Khamene and S. Negahdaripour, "A new method for the extraction of fetal ECG from the composite abdominal signal," *IEEE Trans. Biomed. Eng.*, vol. 47, no. 4, pp. 507–516, Apr. 2000.

[5] J. Leski and A. Gacek, "Computationally effective algorithm for robust weighted averaging," *IEEE Trans. Biomed. Eng.*, vol. 51, no. 7, pp. 1280–1284, Jul. 2004.

[6] Y. Park, K. Lee, D. Youn, N. Kim, W. Kim, and S. Park, "On detecting the presence of fetal R-wave using the moving averaged magnitude difference algorithm," *IEEE Trans. Biomed. Eng.*, vol. 39, no. 8, pp. 868–871, Aug. 1992.

[7] M. Richter, T. Schreiber, and D. Kaplan, "Fetal ECG extraction with nonlinear state-space projections," *IEEE Trans. Biomed. Eng.*, vol. 45, no. 1, pp. 133–137, Jan. 1998.

[8] D. de Araujo, A. Borros, O. Baffa, R. Wakar, H. Zhao, and N. Ohnishi, "Fetal magnetocardiographic source separation using the poles of the autocorrelation function," in *Proc. 4th Int. Symp. Independent Component Analysis and Blind Signal Separation*, 2003, pp. 833–836.

[9] P. Gao, E. Chang, and L. Wyse, "Blind separation of fetal ECG from single mixture using SVD and ICA," Nat. Univ. Singapore, 2004 [Online]. Available: http://www.comp.nus.edu.sg/changec/publications/P0861.pdf

[10] V. Vigneron, A. Paraschiv-Ionescu, A. Azancot, C. Jutten, and C. Sibony, "Fetal electrocardiogram extraction based on non-stationary ICA and wavelet denoising," in *Proc. 7th IEEE Int. Symp. Signal Process. Applicat.*, 2003, pp. 69–72.

[11] M. Burghoff and P. van Leeuwen, "Separation of fetal and maternal magnetocardiographic signals in twin pregnancy using independent component analysis (ICA)," *Neurol. Clin. Neurophysiol.*, vol. 39, pp. 1–4, Nov. 2004.

[12] S. Comani, D. Mantini, A. Lagatta, F. Esposito, S. D. Luzio, and G. Romani, "Time course reconstruction of fetal cardiac signals from fMCG: Independent component analysis versus adaptive maternal beat subtraction," *Physiol. Meas.*, vol. 25, no. 5, pp. 1305–1321, Oct. 2004.

[13] C. Salustri, G. Barbati, and C. Porcaro, "Fetal magnetocardiographic signals extracted by 'signal subspace' blind source separation," *IEEE Trans. Biomed. Eng.*, vol. 52, no. 6, pp. 1140–1142, Jun. 2005.

[14] H. Preissl, C. Lowery, and H. Eswaran, "Fetal magnetoencephalography: Current progress and trends," *Exp. Neurol.*, vol. 190, pp. S28–S36, Nov. 2004.

[15] D. Gutiérrez, A. Nehorai, D. McKenzie, H. Eswaran, C. L. Lowery, and H. Preissl, "On-line fetal heart rate monitoring using SQUID sensor arrays," in *Proc. 14th Biennial BIOMAG Conf.*, 2004, pp. 315–316.

[16] S. Waldert, D. Gutiérrez, A. Nehorai, D. McKenzie, C. Lowery, P. Murphy, H. Eswaran, and H. Preissl, "Real-time access of magnetoencephalographic/cardiographic data: Technical realization and application to online fetal heart rate recording," in *Proc. 27th Annu. Conf. IEEE EMBS*, 2005, vol. 190, p. 28.

[17] P. Comon, "Independent component analysis, a new concept?," *Signal Process.*, vol. 36, no. 3, pp. 287–314, Apr. 1994.
[18] T. Blaschke and L. Wiskott, "CuBICA: Independent component analysis by simultaneous third- and fourth-order cumulant diagonalization," *IEEE Trans. Signal Process.*, vol. 52, no. 5, pp. 1250–1256, May 2004.
[19] T. Hermle, C. Schwarz, and M. Bogdan, "Employing ICA and SOM for spike sorting of multielectrode recordings from CNS," *J. Physiol. Paris*, vol. 98, no. 4–6, pp. 349–356, Nov. 2005.
[20] H. Stögbauer, A. Kraskov, S. Astakhov, and P. Grassberger, "Least dependent component analysis based on mutual information," *Phys. Rev. E Stat. Nonlin. Soft Matter Phys.*, vol. 98, no. 4–6, pp. 349–356, 2004.
[21] A. Hyvärinen and E. Oja, "A fast fixed-point algorithm for independent component analysis," *Neural Comput.*, vol. 9, pp. 1483–1492, Oct. 1997.
[22] A. Hyvärinen and E. Oja, "Independent component analysis: Algorithms and applications," *Neural Netw.*, vol. 13, no. 4–5, pp. 411–433, May 2000.
[23] A. Kraskov, H. Stögbauer, G. Andrzejak, and P. Grassberger, "Hierarchical clustering using mutual information," *Europhys. Lett.*, vol. 70, no. 2, pp. 278–284, Mar. 2005.
[24] A. Kraskov, H. Stögbauer, and P. Grassberger, "Estimating mutual information," *Phys. Rev. E Stat. Nonlin. Soft Matter Phys.*, vol. 69, p. 066 138-1, Jun. 2004.
[25] A. Graps, "An introduction to wavelets," *IEEE Comput. Sci. Eng.*, vol. 2, no. 2, pp. 50–61, Summer, 1995.
[26] J. Vrba, S. Robinson, J. McCubbin, P. Murphy, H. Eswaran, D. Wilson, H. Preissl, and C. Lowery, "Human fetal brain imaging by magnetoencephalography: Verification of fetal brain signals by comparison with fetal brain models," *NeuroImage*, vol. 21, no. 3, pp. 1009–1020, Mar. 2004.
[27] P. van Leeuwen, D. Geue, S. Lange, D. Cysarz, H. Bettermann, and D. Grönemeyer, "Is there evidence of fetal-maternal heart rate synchronization?," *BMC Physiol.*, vol. 3, p. 2, Apr. 2003.

Stephan Waldert received the diploma in bioinformatics from the University of Tübingen, Tübingen, Germany, in 2005. Currently, he is pursuing the Ph.D. degree at the Institute for Medical Psychology and Behavioral Neuroscience/MEG-Center, University of Tübingen, and the Bernstein Center for Computational Neuroscience, University of Freiburg. Scholarship holder of the Studienstiftung des deutschen Volkes.

His research interests are focused on motor learning, brain–machine interfaces, signal processing, and neuroplasticity.

Michael Bensch received the diploma in computer science from the University of Tübingen, Tübingen, Germany, in 2003. Currently, he is pursuing the Ph.D. degree in the Department of Computer Engineering, University of Tübingen.

His research interests are focused on brain–computer interfacing and its applications.

Martin Bogdan received the engineer diploma in signal engineering from the Fachhochschule Offenburg, Offenburg, Germany, in 1993, and the engineer diploma in industrial informatics and instrumentation from the Université Joseph Fourier Grenoble, Grenoble, France, in 1993. He received the Ph.D. degree in computer science (computer engineering) from the University of Tübingen, Tübingen, Germany, in 1998.

In 1994, he joined the Department of Computer Engineering at the University of Tübingen, where he heads the research group NeuroTeam since 2000. This research group deals mainly with signal processing based on artificial neural nets and machine learning focused on but not limited to biomedical applications. Since winter semester 2005/2006, he has been a Substitute Professor for computer engineering at the University of Leipzig, Leipzig, Germany.

Wolfgang Rosenstiel (M'97) received the diploma in informatics and the Ph.D. degree (Dr. rer. nat.) from the University of Karlsruhe, Karlsruhe, Germany, in 1980 and 1984, respectively.

He was an Assistant Professor in the Computer Science Department, University of Karlsruhe, from 1984 to 1986. From 1986 to 1990, he was head of the research group Automation of Circuit Design at the Computer Science Research Center (FZI). Since November 1990, he has been a Professor for informatics (computer engineering) at the University of Tübingen and Director of the Department System Design in Microelectronics at FZI. He is chairman of the edacentrum. His research interests are artificial neural networks and machine learning as well as electronic design automation (EDA) and computer architecture.

Dr. Rosenstiel is the Editor in Chief of the Springer journal *Design Automation for Embedded Systems* and a member of the editorial board of other journals.

Bernhard Schölkopf was born in Stuttgart on February 20, 1968. He received the M.Sc. degree in mathematics from the University of London, London, U.K., in 1992, the diploma in physics from the University of Tübingen, Tübingen, Germany, in 1994, and the doctorate in computer science from the Technical University Berlin, Berlin, Germany, in 1997.

He has researched at AT&T Bell Labs, at GMD FIRST, Berlin, at the Australian National University, Canberra, and at Microsoft Research Cambridge, U.K. He has taught at Humboldt University, Technical University Berlin, and University of Tübingen. In July 2001, he was appointed scientific member of the Max Planck Society and Director at the MPI for Biological Cybernetics; in October 2002, he was appointed Honorarprofessor for Machine Learning at the Technical University Berlin.

Dr. Schölkopf won the University of London's Lionel Cooper Memorial Prize 1992 and the 1997 dissertation prize of the German Association for Computer Science (GI). He also received the prize for the best scientific project at the German National Research Center for Computer Science (GMD), 1998, and the J. K. Aggarwal Prize of the International Association for Pattern Recognition, 2006. He has been program chair of COLT and NIPS and serves on the editorial boards of JMLR, IEEE PAMI, and IJCV.

Curtis L. Lowery received the B.S. degree in biology from the University of Montevallo, Montevallo, AL, in 1977, and the M.D. degree from the University of Alabama at Birmingham School of Medicine, Birmingham, in 1981.

He has been with the University of Arkansas for Medical Sciences, Department of Obstetrics and Gynecology, Division of Maternal-Fetal Medicine, since 1990. In addition, he has collaborated with the Graduate Institute of Technology of the University of Arkansas at Little Rock since 1993 and oversees research projects of graduate students. His areas of interest include noninvasive antepartum surveillance involving superconducting quantum interference device technology, specifically fetal magnetoencephalography, magnetomyography of the gravid uterus, and fetal magnetocardiography. Other areas of interest include percutaneous umbilical blood sampling for prenatal diagnosis and medical management.

Hari Eswaran received the B.S. and M.Sc. degrees in physics (electronics) from the University of Delhi, Delhi, India, the M.S. degree in physics (acoustics) from the University of Mississippi, Oxford, and the Ph.D. degree in applied sciences from University of Arkansas at Little Rock.

He is currently an Assistant Professor and SARA Laboratory Director with the Department of Obstetrics and Gynecology, University of Arkansas for Medical Sciences, Little Rock. His main area of research is focused on biomedical instrumentation with special emphasis on fetal monitoring instrumentation. Other areas of research include evoked potentials, magnetoencephalography, electro- and magnetomyography, acoustics, signal processing, and electronics.

Hubert Preissl received the diploma in physics and the Ph.D. degree in physics, both from the University of Tübingen, Tübingen, Germany, in 1988 and 1994, respectively.

He was with the Max Planck Institute for Biological Cybernetics, Tübingen, until 1994. He then joined the Institute for Medical Psychology and Behavioral Neuroscience, University of Tübingen. In 1997, he became an Assistant Professor with the MEG Center, Tübingen. In addition, since 2000, he has been a Project Director with the Fetal Magnetoencephalography Labratory, Little Rock, AR.