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ECG Extraction by Improved Independent Component Analysis

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Abstract: Independent Component Analysis (ICA) decomposes observed mixed random vectors into statistically independent components while optimizing the contrast function. This study introduces a new automatic method to improve the ICA algorithm and its Signal to Noise Ratio (SNR). As the convergence speed is based on the contrast function, it is improved by optimizing the contrast function with hardware optimization technique. The proposed ICA technique is validated by retrieving the maternal and fetal Electrocardiogram (ECG) signal from their mixtures. Floating-Point (FP) arithmetic calculations are performed to increase the number precision and dynamic range of the signals and hence SNR. Simulation and synthesis are done using Quartus II tool and the algorithm is implemented in Cyclone IVGX Family FPGA. The proposed algorithm operates at a frequency of 2.21 MHz and it provides mean SNR of 47 dB. The proposed method is also implemented in 0.18 um standard cell CMOS technology using Industry standard tool Cadence.

Key words: Adaptive ICA, statistical signal processing, fetal ECG Extraction, VLSI, simulation

INTRODUCTION

A long-standing problem in statistics and related areas is to find a suitable representation of multivariate data. Representation here means that data are transformed so that their hidden, essential content is made more accessible or visible. Blind source separation is a problem of finding a linear representation of hidden data from mixture in which the components are statistically independent. In practical situations, it is not possible to find a representation where the components are really independent but it is possible to find components that are at least as independent as possible. Independent component analysis is a major task in signal processing to extract the source signals from their observed mixtures. The relationship between source signals S and observed mixtures X is given in matrix notation as in Eq. 1:

$$X = AS \tag{1}$$

A is a full rank matrix that is called mixing matrix. Under some assumptions, ICA solves the BSS problem by finding inverse linear transformation such that it maximizes the statistical independence between the observed mixtures. For doing this, ICA finds demixing matrix B which is inverse of mixing matrix A. Then, the estimate of the source signal (S_est) is found from Eq. 2:

$$S_{est} = BX = S \tag{2}$$

i.e., when a mixed signal (X) is multiplied with inverse of mixing matrix, estimate of the original signal (S_est) can be found.

Literature review: The analysis and characterization of biomedical signals is one of the major research areas where the Independent Component Analysis (ICA) has demonstrated a remarkable success. ICA techniques are suitable to solve a large number of biomedical problems like Electrocardiography (ECG) extraction. Electroencephalography (EEG) separation (Makeig *et al*., 1996). Magnetoencephalography (MEG), functional Magnetic Resonance Imaging (fMRI) (McKeown *et al*., 1998) etc. In cardiac signal analysis, ICA methods are employed for separation of Ventricular Activity (VA) and the Atrial Activity (AA) using spatial information (Rieta *et al*., 2004). For enhancing its performance, the separation is also carried out using both temporal and spatial information (Castells *et al*., 2004).

Fetal Magnetoencephalography (fMEG) is a passive, noninvasive method to continuously monitor and investige fetal brain activity to confirm the fetal well-being. Certain aspects of fetal well-being are quantified by the fetal heart signal (Smith and Onstad, 2005). As maternal well-being affects the fetus (Monk *et al*., 2004) the maternal heart signal should be monitored as well. fMEG which is also referred to as magnetocardiography (MCG), contains both the maternal and the fetal heart signals There are

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clinically established. As these clinically established heart-monitoring systems consist of metallic and electronic components, these devices would interfere with the fMEG signal. So they cannot be applied during bio-magnetic measurements. Hence, it is necessary to establish ways that enable fetal and maternal heart monitoring simultaneously.

Extraction of fetal heart signal from the data obtained from fetal magneto-cardiograph and electrocardiography are illustrated (Khamene and Negahdaripour, 2000; Kanjilal *et al*., 1997; Park *et al*., 1992; Richter *et al*., 1998; Leski and Gacek, 2004). Furthermore, analyses are performed by a statistical signal processing technique called Independent Component Analysis (ICA) (Vigneron *et al*., 2003; Gao *et al*., 2004; Comani *et al*., 2004; Burghoff and Leeuwen, 2004; Salustri *et al*., 2005; Preissl *et al*., 2004). Adaptive Real-time ICA algorithm extracts the fetal and maternal heart signal from a noisy and artifact-contaminated data stream in real-time. This algorithm adapts automatically to continuously varying environmental parameters. The main issues associated with existing ICA processes are:

- As Initial weight vectors determine number of iterative calculations, it involves more area and power consumption
- Due to large number of iterations, converging speed of the algorithm is low
- Less work is carried out on Real time ICA processing in VLSI Technology

In this study, Fast Confluence Adaptive ICA proposed and is used for ECG Extraction with hardware optimization technique. The most commonly used Fast ICA algorithm is also validated with ECG signal for comparison purpose. In order to enable the real-time ICA processing in VLSI and to speed up the computation, the ICA algorithms are written by hand coding HDL code where arithmetic operations are performed in floating point arithmetic.

MATERIALS AND METHODS

Ecg sepparation using proposed method: This algorithm performs adaptive optimization of kurtosis based contrast function in floating point arithmetic. The main aim of this algorithm development is to reduce the number of manipulations and to improve the performance of ICA algorithm in terms of convergence speed, area and power. The random number generator unit that requires 32 shift registers is shown in Fig. 1 which has been replaced by an adaptive optimization unit. This adaptive optimization unit updates the weight values based on the kurtosis

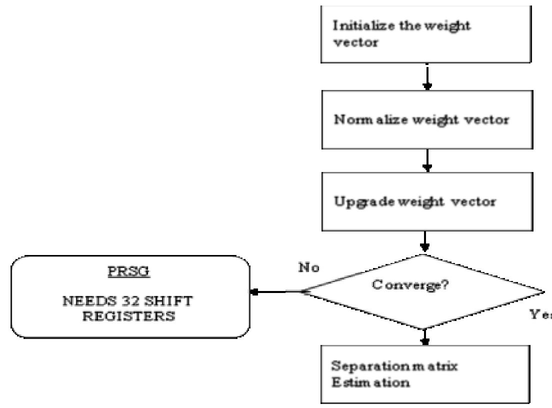

Fig. 1: Existing method

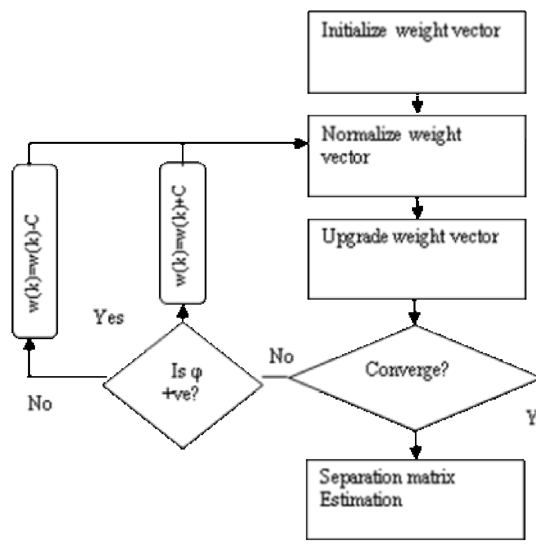

Fig. 2: Proposed method

function to improve the convergence speed. Since adaptive optimization unit contains only the units to increment, decrement and to compare, it involves lesser area and power when compared to random generator unit. In this algorithm, initial weight vectors for estimating the demixing matrix B in (2) are assumed as Wi's. This algorithm computes new weights from the initial weights in adaptive manner based on absolute value of fitness function. The proposed flow of ICA algorithm is shown in Fig. 2.

Fcaica iteration unit: The efficiency of source estimation is based on the selection of cost functions, also called as objective functions or contrast functions. The Cost function in some way or other is a measure of independence (Rieta *et al*., 2004). Some measures of independence are Kurtosis, negentropy and mutual information. Though there are different contrast functions in existence, the most popular contrast function used in ICA is kurtosis. Central limit theorem states that the sum of even two random variables which are independent and identically distributed is more Gaussian than its original form. Hence it can be concluded that non-gaussianity is an efficient measure of independence. Given some random data x, the fourth order moment of that random data is defined as kurtosis which is given in Eq. 3:

$$\text{Kurt}(x) = E\{x^4\} - 3\left(E\{x^2\}\right)^2 \tag{3}$$

where E{.} is the statistical expectation operator. For a Gaussian signal, the fourth moment $E\{x^4\}$ equals to $3(E\{x^2\})^2$ and hence kurtosis is zero. If x is normalized so that variance is equal to unity, then kurtosis is simply the normalized version of the fourth moment as in Eq. 4:

$$\text{Kurt}(x) = E\{x^4\} - 3 \tag{4}$$

Kurtosis value is non-zero for non-gaussian random variables or signals. The weight vector is updated in ICA by the learning rule:

$$W_{newi}(K+1) \leftarrow E\{z \times g(w(k)z^T)\} - E\{z \times g'(w(k)z^T)\} \tag{5}$$

where g( ) is a nonlinear function. Since, derivative of kurtosis can be used as a nonlinear function:

$$g(x)=x^3 \tag{6}$$

On substituting Eq. 6 in Eq. 5:

$$W_{newi}(K+1) \leftarrow E\{z(w(k)z^T)\} - 3E\{z(w(k)z^T)\}^2 \tag{7}$$

Due to the property of unit variance, the Eq. 7 becomes:

$$W_{newi}(K+1) \leftarrow E\{z(w(k)z^T)\} - 3w(k) \tag{8}$$

This is used in main iteration of FCAICA as in Eq. 10. Having done the preprocessing to whiten the mixed signal, this algorithm finds the independent components for extraction of desired signal from the mixtures. The proposed ICA algorithm for one unit estimates one column of the demixing matrix. Updation of weights continues in iterative manner with following steps until a convergence is achieved.

Form a weight matrix W by assuming N sub matrices or column vectors as:

$$W=\{ w1,w2,w3,w4,........wN\}$$

$$wi=(wi1,wi2.........,win)^T$$

Where:

wij = jth weight of ith column vector
n = Number of sources
N = The size of the search space to obtain globally best solution

Find norm of each vector and divide by corresponding norms:

$$\text{Norm}_w = \sqrt{w_1 w_1 + w_2 w_2} \tag{9}$$

Find the updated weight vector Wnew for all the weights in W using Eq. 10 and normalize it:

$$W_{newi}(K+1) \leftarrow E\{z(w(k)z^T)^3\} - 3w_1(k) \tag{10}$$

Calculate the fitness value Φi for all weights:

$$\Phi i = wi(k+1)-wi(k) \tag{11}$$

If $\Phi i < 10^{-4}$, both vectors point in same direction and convergence is achieved. Then w_{new} is one of the column vectors of demixing matrix to estimate first independent component. If $\Phi i > 10^{-4}$, divide the N weight vectors into M sorted groups (N = 2M) with 2 (n = 2) weights in each group. The division is done in such a way that 1st weight goes to 1st group, 2nd weight goes to 2nd group and continuous up to M weight. Then (M+1)th weight goes to 1st group and so on. In each group, If Φi (k)<Φi (k+1) then:

$$\text{refi}(k)= \Phi i\ (k) \tag{12}$$

else

$$\text{refi}(k)= \Phi i\ (k+1)$$

end

If refi (k) is positive:

$$wi(k)= wi(k)-C \tag{13}$$

else

$$wi(k)=wj(k)+C$$

end

where, C is a random nonnegative floating point number between ‘0’ and ‘1’. Repeat from step 2 to find wi(k+1) until convergence is achieved.

Deflationary orthogonalization: To find more than one independent component, deflationary orthogonalization is done before step 4 of the iteration process:

$$w_p \leftarrow w_p - \sum_{j=1}^{p-1} \left(w_p^T w_j\right) w_j \tag{14}$$

The othogonalization is made to ensure that rows w_j of separating matrix are orthogonal. This verification is done by subtracting all previously estimated vectors from the current estimate w_p before normalization as in Eq. 14. It is known that the convergence speed of fast ICA is cubic or atleast quadratic. Based on the fitness value of each assumed weight vector, the direction of the desired search space is found which excludes unnecessary searching area. As the search space has been reduced, the convergence time has also been reduced without affecting the quality of the optimal solution.

Once the convergence is achieved, the two vectors with good fitness value are used as column vectors of demixing matrix B. This B is then used to find the estimate of source signal. While finding more than one independent component, deflationary othogonalization should be made to ensure that the same independent components are not estimated more than once. The floating point operations enhance the quality of optimal solution.

Fcaica architecture: Proposed power efficient, area efficient and cost-effective floating point FCAICA architecture is shown in Fig. 3. The input ports of the module consist of an observed signal, 1-bit reset signal, 1-bit start signal and a 1-bit clock pulse that synchronizes the interconnected RCs. 1-bit Done signal which is at the output port is enabled when independent Components are separated. Estimates of the source signal are at the output ports.This architecture has simple arrows to represent the main block control precedence and block arrows to denote the data flow. The architecture consists of three parts: centering unit, whitening unit and the iteration unit. They operate sequentially and shares same data memory. According to the algorithm, memory is needed also to store old weight matrix and new weight matrix. The architecture in Fig. 3 shows that, the input data are stored in the data memory. Then, the data are fetched from the data memory to perform centering

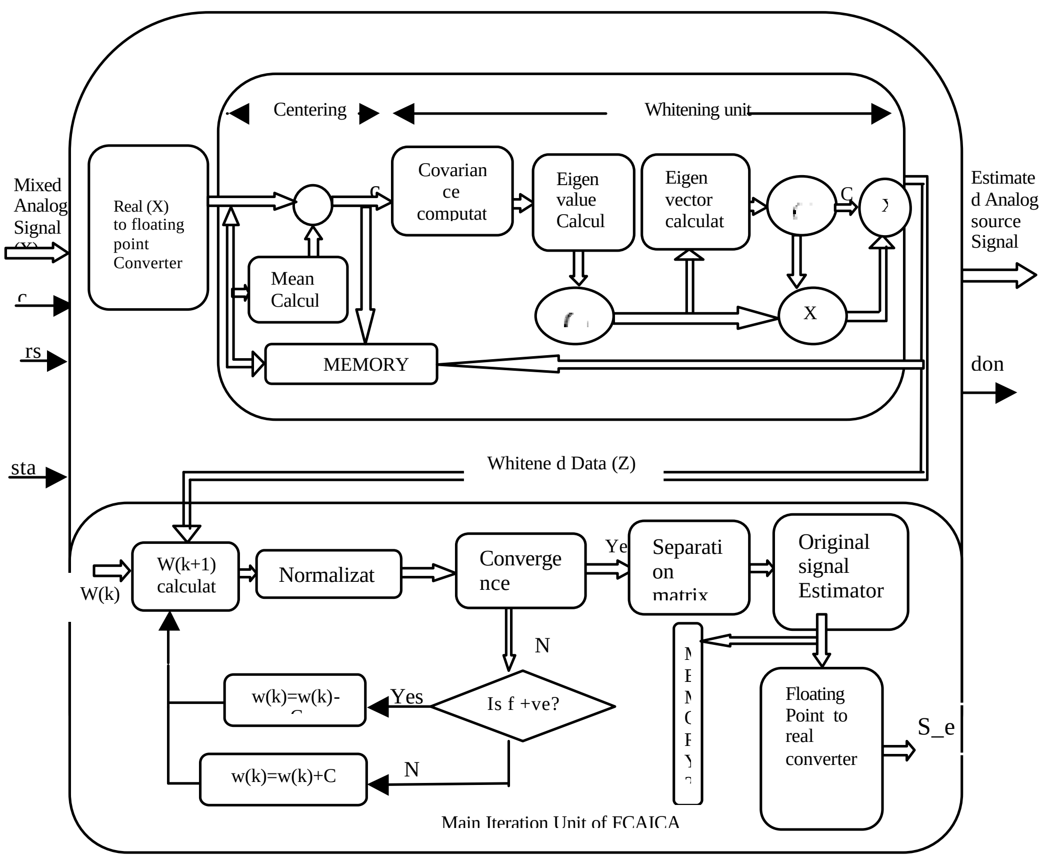

Fig. 3: Architecture of proposed ICA aglgorithm

through the centering unit. Centering subtracts mean of the mixtures from each observed samples $X_1(t)\ldots X_N(t)$ to produce zero mean outputs. The second step is called Whitening and consists in linear transformation of the centered data to obtain new white vectors. It is done through covariance, eigenvalue and eigenvector calculators. One of the ways to perform whitening is to use EVD which is defined as:

$$E\left[XX^T\right] = C_X = EDE^T \tag{15}$$

Where:

E = A statistical expectation operator
E = The orthogonal matrix of eigenvectors $\{ ei \}$ of C_X
C_X = The covariance matrix of X
D = Diag($\{di\}$) is the diagonal matrix of its eigen values

Then the whitening matrix is found from Eq. 11:

$$P = D^{-1/2} E^T \tag{16}$$

The whitening matrix P is found from eigen values and eigen vectors. The whitening process is completed by finding whitened vector Z from:

$$Z = PX \tag{17}$$

The components of a whitened vector are uncorrelated and their variances equals to unity. This means that the covariance matrix of whitened data is equal to identity matrix.The whitened data produced by the whitened data generator are written back to the data memory. Thus, the pre-processing step is completed. The next process is to perform iteration to meet convergence. Initially assumed weights are sent to normalization unit after updating using Eq. 10. The convergence is checked through the convergence checking unit. On satisfying the convergence threshold or reaching the maximum iteration, the iteration process is terminated and the data are sent to separation matrix estimator to estimate the source signals. Otherwise adaptive optimization unit checks the fitness parameter for having positive or negative value. If the difference value is positive then a non-negative floating point number (C) is subtracted from the assumed weight vector to get new weight.

If the difference value is negative then a non negative floating point number (C) is added to the assumed weight vector to get new weight. This iteration process is repeated until convergence is reached or maximum iteration limit is reached. The resulting weight vectors forms one column of the demixing matrix(B). The demixing matrix is multiplied with the mixture input to get estimate of source signal (S_est) as in Eq. 2. Finally, the separated signals are written back to the data memory MEMORY2. The reduction in area and improvement in convergence speed is achieved by eliminating the random generator unit present in conventional ICA and replacing it by adaptive optimization unit.

The three main Reconfigurable Components (RC) weight vector updating unit, convergence check unit and separation matrix calculator unit are developed individually and integrated together to form a complete module.

RESULTS AND DISCUSSION

For validating the functionality of the algorithm, extensive simulations were carried out on ECG mixtures.

Parameter setting: For fine-tuning this category of problem to real world applications, these experiments were carried out with different set of parameters. In the experimental studies, the number of initial weight vectors selected is eight (N = 8). The number of weight vectors in each group is 2, since the number of sources observed is 2. At first, mixtures of maternal ECG and Fetal ECG are applied to the algorithm. The input signals applied to these ICA algorithms are sampled at 4kHz. Mixing matrix A selected for this problem is of rank 2 and given by:

$$A = \begin{bmatrix} 0.5 & 0.3 \\ 0.7 & 0.2 \end{bmatrix}$$

The mixtures are shown in Fig. 4 and 5. The experiment was carried out for the problem with 30,000 samples. Figure 6 and 7 shows the independent components obtained through the ICA algorithms.

SNR and convergence analysis: The SNR values are 46.68 and 50.27 dB for maternal ECG and fetal ECG, respectively which is fine enough to acquire the same quality as the original sources. It is to be noted that, the SNR obtained with fixed point Fast ICA is 16dB. The

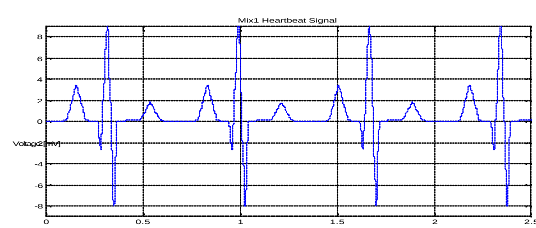

Fig. 4: Mixture of ECG signal 1

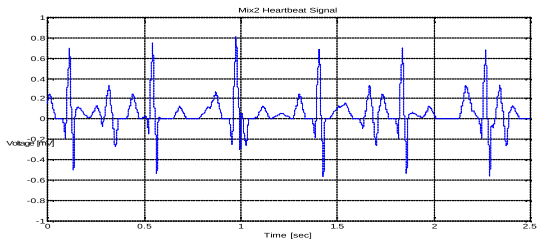

Fig. 5: Mixture of ECG 2

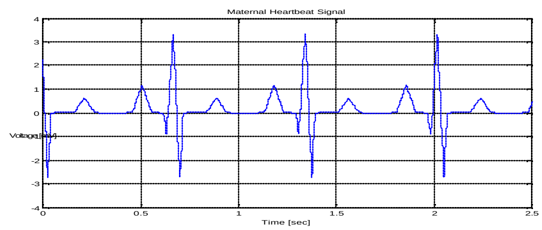

Fig. 6: Recovered maternal ECG signal

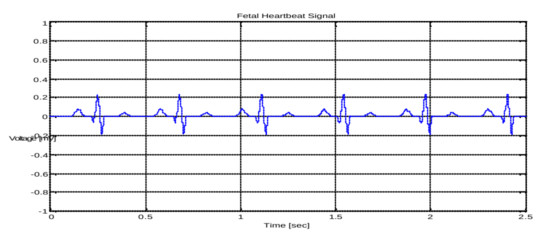

Fig. 7: Recovered Fetal ECG signal

usage of floating point arithmetic operations significantly improves the SNR of Blind Source Separation problems.

The convergence speed analysis is done with the simulation results obtained from Cadence NCsim Tool v10. Convergence speed represents the time taken for each of the algorithms to reach convergence. It is achieved when a vector w(k-1) and its updated vector w(k) are pointing in the same direction. From the simulation results, it is observed that the proposed ICA gives the best results, when compared with the existing methods

Implementation results of ica algorithms: Algorithms are written in very high speed integrated circuit Hardware Description Language (VHDL) and simulated using Cadence Tool. Floorplanning, Placement, Routing and post route simulation are carried out with "rc" and "encounter" cadence tools after successful completion of synthesis. It is also implemented in ALTERA FPGA using Quartus II 11.1 Tool. Table 1 gives performance comparison obtained from Cadence Tool. It also provides information about the area and power consumption of

Table 1: Comparative analysis between the existing and proposed methods

Parameters	Cell instance	Area	Total power (mW)	Operating frequency (MHz)
FCAICA	6349	112871	12.092	2.91
Proposed ICA	6242	110969	10.13	3.2

ICA algorithms and its comparison with proposed method. Due to the reduced complexity of adaptive optimization unit, the resource utilization and power consumption is reduced and the operating speed is increased in Proposed ICA.

CONCLUSION

In this research, new time-domain approach to extract the maternal ECG and Fetal ECG form the mixture with improved convergence speed and SNR has been presented. The hardware optimization of algorithms enables finding global optimal solution. This algorithm uses a new robust objective function optimization to improve the separation performance. Floating point manipulations enable increased dynamic range and improved SNR. The peculiarity of the resulting system is the capability of providing faster convergence with improved SNR. VLSI design concepts like modularity and hierarchy simplify the design and speed up the ICA process.

Further research includes the application of the proposed method for other signals such as EEG, Spread spectrum signals and images under poor SNR circumstances. Further improvement is possible by employing this technique with sources more than two.

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