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A New Design And Implementation On Convolution Blind Source Seperation

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ABSTRACT

Brief presents an efficient very-large-scale integration architecture design for convolutive blind source separation (CBSS). The CBSS separation network derived from the information maximization (Infomax) approach is adopted. The proposed CBSS chip design consists mainly of Infomax filtering modules and scaling factor computation modules. In an Infomax filtering module, input samples are filtered by an Infomax filter with the weights updated by Infomax-driven stochastic learning rules. As for the scaling factor computation module, all operations including logistic sigmoid are integrated and implemented by the circuit design based on a piecewise-linear approximation scheme. The proposed prototype chipis implemented via a semicustom design using90-nmCMOS technology on a die size of approximately 0.54×0.54 mm2.

I. INTRODUCTION

Blind source separation (BSS) attempts to separate sources from mixed signals when most of the information for sources and mixing process is unknown. Such restrictions make BSS a challenging task for researchers. BSS has become a very important research topic in a lot of fields. Notable examples include audio signal processing, biomedical signal processing, communication systems, and image processing . Without a filtering effect, instantaneous mixing is considered a simple version of the mixing process of the source signals. However, for audio sources passing through an environmental filtering before arriving at the microphones, a convolutive mixing process occurs, and convolutive BSS (CBSS) is used to recover the original audio sources. Independent component analysis (ICA) is the conventional means of solving the BSS or CBSS problem. However, this method is often highly computationally intensive and introduces time-consuming processes for software implementation. More than a faster solution than software implementation, hardware solution achieves optimal parallelism. Providing hardware

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solutions for ICA-based BSS has drawn considerable attention recently. Cohen and Andreou explored the feasibility of combining above-andsubthreshold CMOS circuit techniques for implementing an analog BSS chip that integrates an analog I/O interface, weight coefficients, and adaptation blocks. This chip incorporates the use of the Herault–Jutten ICA algorithm. Cho and Lee implemented a fully analog CMOS chip based on information maximization (Infomax) ICA, as developed by Bell and Sejnowski. The chip incorporated a modular architecture to extend its use as a multichip. Apart from these analog BSS chips, various fieldprogrammable gate array(FPGA) implementations with digital architectures have been developed. Li and Lin realized the Infomax BSS algorithm based on system-level FPGA design, by using Quartus II, DSP builder, and Simulink. Du and Qi presented an FPGA implementation for the parallel ICA (pICA) algorithm, which focuses on reducing dimensionality in hyperspectral image analysis. The pICA algorithm consists of three temporally independent functional modules that are synthesized individually with some reconfigurable components developed for reuse. Based on Infomax BSS, Ounas et al. introduced a low-cost digital architecture implemented on FPGA. This design used merely one neuron to support sequential operations of the neurons in neural network. In 2008, Shyu et al.designed a pipelined architecture for FPGA implementation based on FastICA for separating mixtures of biomedical signals, including electroencephalogram (EEG), magneto encephalography (MEG), and electrocardiogram (ECG). In this design, floating-point arithmetic units were used to increase the precision of the numbers and ensure the FastICA performance.

II. LITERATURE SURVEY

Separating brain imaging signals by maximizing their autocorrelations is an important component of blind source separation (BSS). Canonical correlation analysis (CCA), one of leading BSS techniques, has been widely used for analyzing optical imaging (OI) and functional magnetic resonance imaging (fMRI) data. However, because of the need to reduce dimensionality and ignore spatial autocorrelation, CCA is problematic for separating temporal signal sources. To solve the problems of CCA, "straightforward image projection" (SIP) has been incorporated into temporal BSS. This novel method, termed low-dimensional canonical correlation analysis (LD-CCA), relies on the spatial and temporal autocorrelations of all genuine signals of interest. Incorporating both spatial and temporal information, here we

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introduce a "generalized timecourse" technique in which data are artificially reorganized prior to separation. The quantity of spatial plus temporal autocorrelations can then be defined. By maximizing temporal and spatial autocorrelations in combination, LD-CCA is able to obtain expected "real" signal sources. Generalized timecourses are low-dimensional, eliminating the need for dimension reduction. This removes the risk of discarding useful information. The new method is compared with temporal CCA and temporal independent component analysis (tICA). Comparison of simulated data showed that LD-CCA was more effective for recovering signal sources. Comparisons using real intrinsic OI and fMRI data also supported the validity of LD-CCA. Online blind source separation (BSS) is proposed to overcome the high computational cost problem, which limits the practical applications of traditional batch BSS algorithms

III PROPOSED VLSI BLIND SOURCE SEPARATOR

The proposed CBSS system is shown in the FIG.1. The CBSS chip mainly consists of two functional cores: Infomax filtering module and scaling factor computation module. Additionally, the Infomax filtering outputs are added with the help of two small carry-save adders (CSAs). The current prototype chip is used for two sources and two sensors by utilizing four Infomax filtering modules along with two scaling factor computation modules.

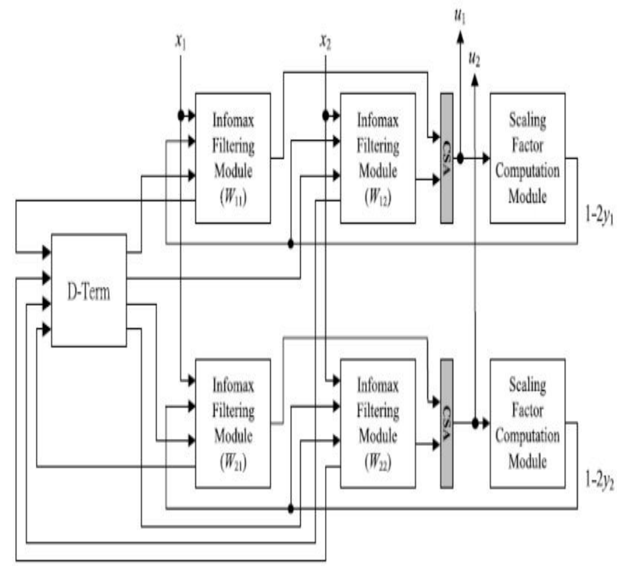

FIG. : The block diagram of a proposed CBSS system.

IV INFOMAX FILTERING MODULE

The Infomax filtering module for the proposed system is shown in fig.2. the CBSS separation network contains four causal FIR filters. These filters are adaptive because stochastic learning rules which are derived from the Infomax approach will alter the tap coefficients and are thus referred to herein as the Infomax adaptive filter or the Infomax filter. The Infomax filtering module is exemplified with six taps. In the

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Infomax filtering module, an input sample passes through lower and upper register chains. These samples are multiplied with filter weights and scaling factors, respectively. The multiplication results of all of the taps are accumulated by a two-stage summation. The first stage adopts carry lookahead adders to generate the intermediate addition results for multiplication of every two successive taps. The above intermediate addition results are summed up by using a carry save addition scheme. A CSA(carry save adder) can accept more than two data inputs.

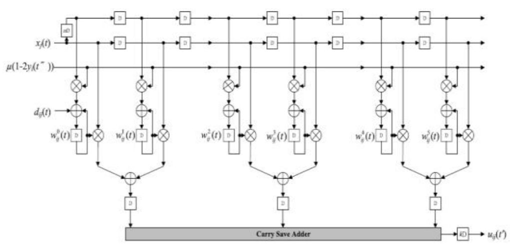

fig.2.

INFOMAX FILTERING

V CONCLUSION

An efficient VLSI architecture design for CBSS with less delay has been presented in this paper. The architecture mainly consists of Infomax filtering modules and scaling factor computation modules and a D-term. CBSS separation network derived from the Infomax approach. The proposed system has high performance and has less delay as compared with the other existing system. By the usage of vedic multiplier in Infomax filter increases the speed as well as performance of the proposed system.

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