Proceedings of the 28th IEEE
EMBS Annual International Conference
New York City, USA, Aug 30-Sept 3, 2006

An adaptive multiple-input multiple-output analog-to-digital converter for high density neuroprosthetic electrode arrays

Shantanu Chakrabartty, *Member, IEEE,* Amit Gore, Karim G. Oweiss, *Member, IEEE*

***Abstract*—On chip signal compression is one of the key technologies driving development of energy efficient biotelemetry devices. In this paper, we describe a novel architecture for analog-to-digital (A/D) conversion that combines sigma delta conversion with the spatial data compression in a single module. The architecture called multiple-input multiple-output (MIMO) sigma-delta is based on a min-max gradient descent optimization of a regularized cost function that naturally leads to an A/D formulation. Experimental results with simulated and recorded multi-channel data demonstrate the effectiveness of the proposed architecture to eliminate cross-channel redundancy in high density microelectrode data, thus superceding the performance of parallel independent data converters in terms of its energy efficiency.**

I. INTRODUCTION

Neuroprosthetic devices and Brain Machine Interfaces (BMIs) play a vital role in helping patients with severe motor disorders achieve a better lifestyle by enabling direct interface to the central nervous system at various levels. Invasive interfaces generally consist of an array of microelectrodes implanted subcutaneously to record electrical signals from neural structures of interest and selectively stimulate others. Most implantable electrode arrays interface with a biotelemetry system that consists of an array of analog-to-digital converters for digitizing and transmission of recorded data. Current advances in microfabrication technology have greatly accelerated the integration of high-density microelectrode arrays on a single device[1]. A typical state-of-the-art microelectrode array can have as many as 1000 electrodes integrated on a single device which significantly increases bandwidth requirements and hence power dissipation of the biotelemetry system. Next generation of prosthesis will host even larger number of electrodes and recording channels considering that approximately 30,000 neurons and 2.4×10^8 synapses (assuming 8,000 synapses/neuron) may exist in a cubic millimeter of cortex tissue [2]. Thus high data throughput requirement will necessitate signal compression functionality to be embedded directly on the sensor. Fortunately due to the characteristics of the extra-cellular surroundings and the array design constraints [1], large correlation is observed among noise processes across adjacent electrode channels. Moreover, if the array is closely spaced, signals may exhibit significant correlation as well. Thus signal compression at the sensor can be achieved by using a spatio-temporal compression of neural signal, which had been a focus of our previous work. [3].

In this paper we describe architecture of a novel MIMO sigma-delta converter that combines analog-to-digital conversion with adaptive spatial compression. The architecture has significant advantages over conventional multi-channel A/D that are rigid and have minimal calibration ability to utilize spatial correlation between channels for data conversion. This procedure not only reduces the required data throughput but also reduces power dissipation of the front-end by eliminating redundant data converter paths.

The paper is organized as follows: Section II first introduces an optimization based framework to illustrate the concept of parallel sigma delta conversion. Section III then uses the framework to obtain the architecture for the proposed MIMO sigma delta conversion. Section IV describes experimental results obtained using the MIMO sigma delta converter, based on recorded multi-channel neural data. Section V concludes with some final remarks.

II. REGULARIZATION FRAMEWORK AND $\Sigma\Delta$ CONVERTERS

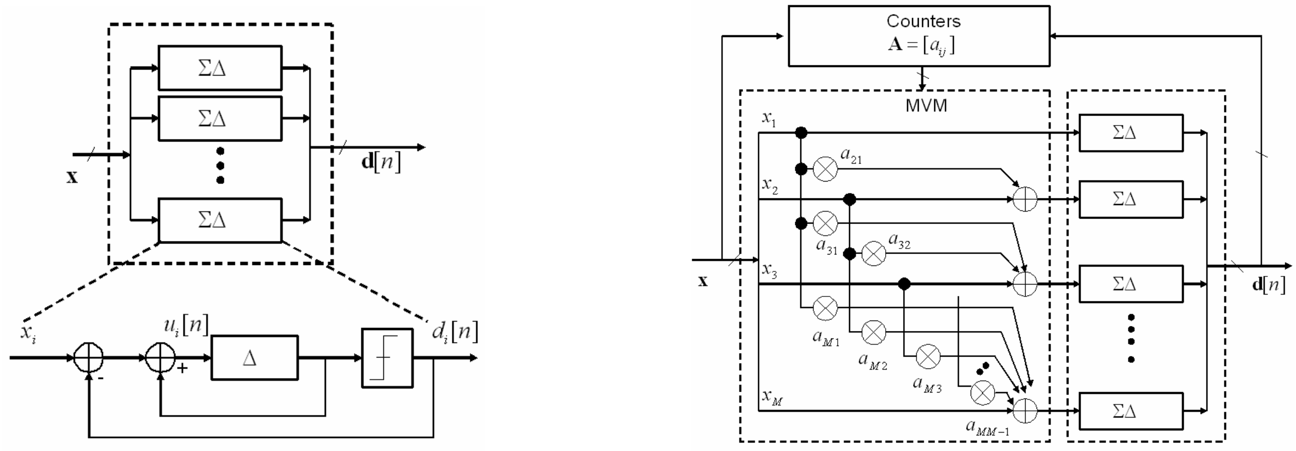
In this section we introduce an optimization framework for deriving first-order sigma-delta converters. For the sake of simplicity we will first assume that the input to converter is a M dimensional vector $\mathbf{x} \in \Re^M$ that is constant with respect to time. We will show in the next section that this assumption is reasonable for oversampling data converters and we will extend the framework to introduce temporal variations. Let $\mathbf{u} \in \Re^M$ represent an internal state vector which is used by the parallel converter to produce digital representation. Consider a regularized optimization problem given by

$$\min_{\mathbf{u}} f(\mathbf{u}) = \min_{\mathbf{u}} |\mathbf{u}|^T \mathbf{1} - \mathbf{u}^T \mathbf{x} \qquad (1)$$

where $\mathbf{1}$ represents a vector whose elements are unity.

Manuscript received April 3, 2006.

The authors are with the ECE Dept., Michigan State University, East Lansing, MI 48824 USA (Phone: 517-432-5679; fax: 517-353-1980; e-mail: shantanu@msu.edu).



(a) *(b)*

Figure 1. (a) Architecture of a conventional multi-channel sigma-delta converter and its architecture (b) architecture of the proposed MIMO sigma-delta converter.

The cost function (1) consists of two factors: the first factor is a L_1 regularizer which constrains the norm of the vector $\mathbf{u}$ and the second factor that maximizes the correlation between vector $\mathbf{u}$ and the input signal vector $\mathbf{x}$. Similar to optimization functions used in machine learning [5] the cost function (1) models a solution $\mathbf{u}$ which is correlated to the input (minimize reconstruction error) and at the same time is bounded (regularized). The use of L_1 regularizer also endows the gradient of $f(\mathbf{u})$ with a signed representation of vector $\mathbf{u}$. An online gradient descent procedure for minimizing (1) is given as

$$\mathbf{u}[n]=\mathbf{u}[n-1]-\eta\frac{\partial f}{\partial \mathbf{u}} \quad (2)$$

where $\mathbf{u}[n]$ denotes an online estimate of $\mathbf{u}$ at time instant n, $\partial f/\partial \mathbf{u}$ is an online estimate of the gradient and η is a learning rate. Using equation (1) the update rule (2) can be written as

$$\mathbf{u}[n]=\mathbf{u}[n-1]+\eta(\mathbf{x}-\mathbf{d}[n]) \quad (3)$$

where

$$\mathbf{d}[n]=\mathrm{sgn}(\mathbf{u}[n-1]) \quad (4)$$

and $\mathrm{sgn}(\mathbf{u})$ denotes an element-wise sign operation such that $\mathbf{d}[n]\in\{+1,-1\}^M$. Equation (3) represents the recursion step for M independent first-order sigma delta converters [4]. As in sigma-delta architecture it can be shown that for bounded inputs $|x_i|\leq 1 \Rightarrow |u_i|\leq 1+\eta$ the magnitude of the state variable is bounded [4]. After N update steps the recursion (3) yields

$$\mathbf{x}-\frac{1}{N}\sum_{n=1}^{N}\mathbf{d}[n]=\frac{1}{\eta N}(\mathbf{u}[N]-\mathbf{u}[0])$$

which after using the bounded property of $\mathbf{u}$ leads to

$$\frac{1}{N}\sum_{n=1}^{N}\mathbf{d}[n]\xrightarrow{N\to\infty}\mathbf{x}.$$

Therefore consistent with theory of sigma delta conversion the moving average of vector digital sequence converges to the input vector $\mathbf{x}$ as the number of update steps increase. It can also be shown that N update steps yield a digital representation which is $\log_2(N)$ bits accurate. The architecture of a first order sigma delta converter is shown in Figure 2(a) which also shows signal flow architecture for implementing the recursion (3). In the next section we modify the architecture in 2(a) for a general MIMO sigma-delta converter based an augmented optimization criterion.

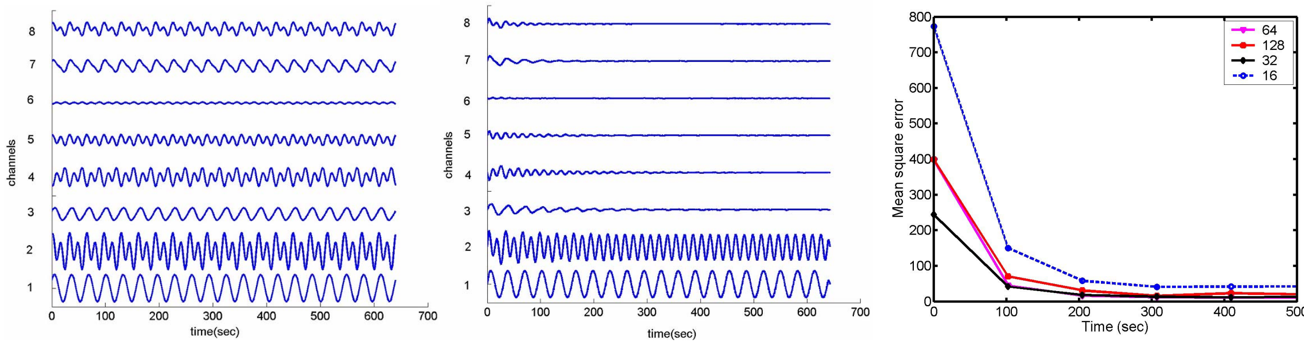
III. First order MIMO ΣΔ converters

A general framework for a MIMO sigma delta converter is obtained by augmenting the cost function (1) by a de-mixing matrix $\mathbf{A}\in\Re^{M\times M}$ and is given by

$$f(\mathbf{u},\mathbf{A})=|\mathbf{u}|^T\mathbf{1}-\mathbf{u}^T\mathbf{A}\mathbf{x}. \quad (5)$$

The cost function (1) is a special case of (5) for the de-mixing matrix to be an identity matrix. The form of $\mathbf{A}$ is important to ensure uniqueness of the solution. In our approach $\mathbf{A}=[a_{ij}]$ is chosen to be a lower triangular matrix such that $a_{ij}=0; i<j$ and $a_{ij}=1; i=j$.

.



(a) (b) (c)

Figure 3: Functional verification of MIMO sigma-delta converter : (a) Artificially generated multi-channel input data (b) Analog representation of digital output produced by MIMO converter (c) Reconstruction error in terms of mean square error incurred for different OSR.

The optimization problem for MIMO sigma delta converter is given by a min-max optimization criterion

$$\max_{a_{ij}:i\neq j}(\min_{\mathbf{u}} f(\mathbf{u},\mathbf{A})) \tag{6}$$

which is equivalent to simultaneously minimizing reconstruction error and the cross correlation between channels. An advantage of using a lower triangular matrix with diagonal elements as unity is that its inverse always defined and hence can be used for reconstruction. The gradient descent steps to optimize (5) according to (6) is given by

$$\mathbf{u}[n]=\mathbf{u}[n-1]-\eta(\mathbf{A}[n-1]\mathbf{x}-\mathbf{d}[n]) \tag{7}$$

$$\mathbf{d}[n]=\mathrm{sgn}(\mathbf{u}[n-1]) \tag{8}$$

and the gradient ascent update for the matrix $\mathbf{A} = [a_{ij}]$ is given by

$$a_{ij}[n]=a_{ij}[n-1]-\varepsilon u_i[n]x_j \quad \forall i>j. \tag{9}$$

where ε is a learning rate parameter. The online rule (8) can be simplified using only the sign of the state variable $\mathbf{u}$ and the input vector $\mathbf{x}$ as

$$a_{ij}[n]=a_{ij}[n-1]-\varepsilon d_i[n]\mathrm{sgn}(x_j) \quad \forall i>j. \tag{10}$$

The update rule can be implemented using digital logic and counters and obviates the requirement for additional analog-to-digital conversion steps to convert the de-mixing matrix elements into digital domain. The update rule (10) bears strong resemblance to update rules used in independent component analysis (ICA) [6]. The architecture for the proposed MIMO sigma delta converter is shown in Figure 2(b), which consists of a matrix vector multiplier for transforming the input vector using a lower triangular de-mixing matrix according to equation (7). In the architecture 2(b) the first channel is chosen as a reference based on which other de-mixing matrix elements are computed. Even though any channel can be chosen as a reference channel, our experiments indicate that the channel with maximum cross-correlation and maximum signal power serves as the best choice.

The output of the MIMO sigma delta converter is a digital stream whose pulse density is proportional to the transformed input data vector as

$$\frac{1}{N}\sum_{n=1}^{N}\mathbf{d}[n]\xrightarrow{N\to\infty}\mathbf{A}\mathbf{x}. \tag{11}$$

By construction of the optimization problem (6) and the transformation equation (11), the MIMO converter produces a digital stream whose analog representation eliminates any redundant cross-channel information using a linear transform represented by matrix $\mathbf{A}$. Some of the digital channels can therefore be discarded. The original signal can be reconstructed from the digital stream using an inverse transform and is given by

$$\hat{\mathbf{x}}=\frac{1}{N}\mathbf{A}^{-1}\sum_{n=1}^{N}\mathbf{d}[n]. \tag{12}$$

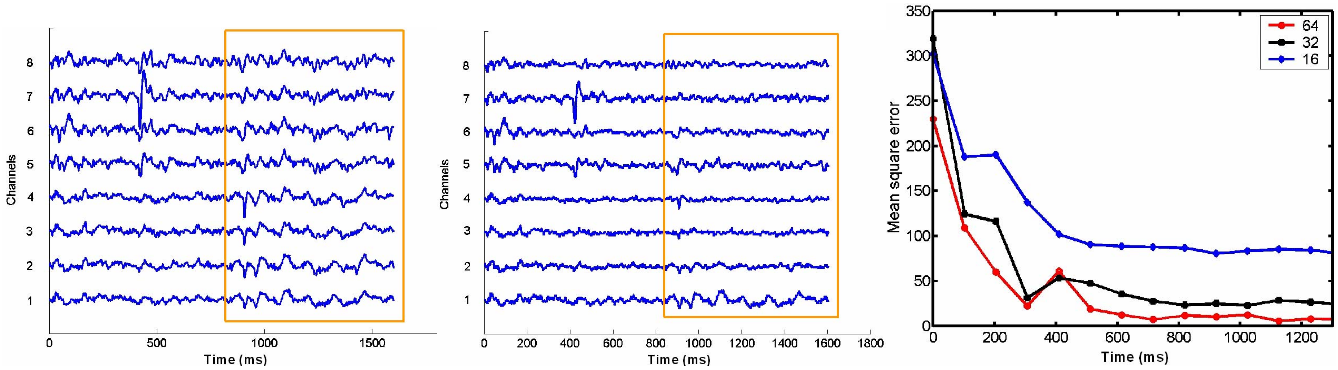
The framework of MIMO sigma-delta converter is still valid for time varying inputs where equation (11) is modified as

$$\frac{1}{N}\sum_{n=1}^{N}\mathbf{d}[n]\xrightarrow{N\to\infty}\frac{1}{N}\sum_{n=1}^{N}\mathbf{A}\mathbf{x}[n]$$

If the oversampling rate (OSR) which is the ratio of the sampling frequency (update frequency) to Nyquist rate is much greater than 1, then the moving average of the digital sequence can track the transformed input signal [4]. The variation of de-mixing matrix $\mathbf{A}$ is assumed to be a much slower varying process and is not required to be transmitted for reconstruction, unless large variations in cross-channel statistics is encountered.

IV. Results

The functionality of the proposed MIMO sigma-delta converter was verified using artificially generated data and with real multi-channel recorded neural data.



(a) (b) (c)

Figure 4: Functional verification of the MIMO sigma-delta converter for multi-channel neural data: (a) Original multi-channel data (b) analog representation of digital output produced by the converter (c) reconstruction error in terms of mean square error for different OSR.

For the first set of experiments an 8 channel multi-channel data was artificially generated. Figure 3(a) illustrates the multi-channel data where each channel is a random mixture of sinusoids with frequency 20Hz and 40Hz. The multi-channel data was presented to a MIMO sigma delta converter implemented in software and the output digital stream was combined using a moving window averaging technique with window size equal to the oversampling ratio (OSR). The resultant analog representation is shown in Figure 3(b). It can be seen in the figure that after initial adaptation steps the output corresponding to first two channels converges to the fundamental sinusoids, where as the rest of the digital streams converged to an equivalent zero output. Thus this simple experiment demonstrates the functionality of MIMO sigma-delta to eliminate cross-channel redundancy. The first two digital streams were used to reconstruct the original recording using equation (12). Figure 3(c) shows the reconstruction error averaged over a time window of 2048 samples showing that the error indeed converges to zero, as the MIMO converter adapts.

Similar experiments were repeated with an eight channel neural data recorded from dorsal cochlear nucleus of adult guinea pigs. The data was recorded at a sampling rate of 20KHz and at a resolution of 16 bits. Figure 4(a) shows a clip of multi-channel recording for duration of 1.5 seconds. It can be seen from highlighted portion of Figure 4(a) that the data exhibits high degree of cross-channel correlation. Similar to the first experiment the MIMO converter output eliminates spatial redundancy between channels. An interesting observation in this experiment is that even though the statistics of the input signals were varying in time as shown in Figure 4(a) and (b), the de-mixing matrix remains stationary during the duration of the conversion, which is illustrated through the reconstruction error graph in Figure 4(c). This validates the principle of operation of the MIMO converter where the multi-channel neural recording lie on a low-dimensional manifold whose parameters are relatively stationary with respect to the signal statistics.

V. CONCLUSIONS

In this paper we presented architecture of a novel MIMO sigma-delta converter that can be used for high density neural recording and biotelemetry applications. We have demonstrate the utility of the converter in eliminating cross-channel redundancy whereby reducing data throughput requirements and equivalently the power dissipation of any biotelemetry device.

REFERENCES

[1] K. Wise *et. al.*, **"**Wireless Implantable Microsystems: High-Density Electronic Interfaces to the Nervous System," *Proc. of the IEEE*, Vol.: 92-1, pp: 76–97, Jan. 2004

[2] V. Braitenberg and A. Schuz, *Cortex: Statistics and Geometry of Neuronal Connectivity*. New York: Springer-Verlag, 1998

[3] K. Oweiss, D. Anderson, M. Papaefthymiou, " Optimizing Signal Coding in Neural Interface System-on-a-Chip Modules," *IEEE Conf. on EMBS*, pp. 2016-2019, Sept. 2003

[4] J. C. Candy and G. C. Temes, "Oversampled methods for A/D and D/A conversion," in *Oversampled Delta-Sigma Data Converters*. Piscataway, NJ: IEEE Press, 1992, pp. 1-29.

[5] Girosi, F., Jones, M. and Poggio, T. "Regularization Theory and Neural Networks Architectures," *Neural Computation*, vol. 7, pp 219-269, 1996

[6] Hyvärinen, A. (1999e). Survey on independent component, analysis. *Neural Computing Surveys*, 2:94–128.