High Performance Magnetic Field Smart Sensor Arrays With Source Separation

A. Paraschiv-Ionescu[1], C. Jutten[1], A.M. Ionescu[2], A. Chovet[2], A. Rusu[3]
[1]LIS, INPGrenoble, 46, av. Félix Viallet, 38031 Grenoble, France
[2]LPCS/ENSERG, 23, rue des Martyrs, BP 257, 38016 Grenoble, France
[3]Polytechnic University of Bucharest, Electronic Dept., 313, Splaiul Independentei, Romania

I. ABSTRACT

A new approach to design high performance microsystems is proposed. It is based on the association between a low-cost sensor array and a multidimensional signal processing technique: the so-called *'blind source separation'*. In order to illustrate the effectiveness of the method, we applied the source separation processing for a Hall-type silicon sensor array in order to cancel the temperature cross-sensitivity and spurious magnetic field sources crosstalk. A microsystem prototype including the Hall sensor array, conditionning electronics and a DSP running source separation algorithm is currently designed.

Keywords: Hall-device sensor array, source separation, cross-sensitivity cancellation, crosstalk cancellation, smart microsystem.

II. INTRODUCTION

One of the main goals of smart microsensor design is to eliminate the cross-sensitivities and the crosstalk which are major drawbacks for providing higher accuracy and higher resolution sensors [1]. Classical solutions are the so-called 'sensor within a sensor' (compensation method) and tailored correction method [1], [2]. In this paper we propose a new approach in order to design low-cost high performance sensor systems. The method is based essentially on the association of a low-cost sensor array with a fairly new signal processing technique: the blind source separation.

Blind source separation *(BSS)* consists in recovering *unobserved* signals (the sources) from *observed* mixtures (typically, outputs of an array of sensors) *without knowing* the mixing coefficients. Many theoretical results and practical algorithms are now available according to this approach [3], [4], [5], [6], [7], [8]. Provided that there are at least as many sensors as sources, these algorithms estimate simultaneously unknown sources from observed mixture. Thus, using a sensor array, the source separation methods are good candidates to cancel the sensor cross-sensitivities and the sensor crosstalk (due to a few spatial sources of same type).

In this paper the source separation method is applied to a Hall-type silicon sensor array, but it could be applied for any type of sensor array.

III. SOURCE SEPARATION

A. The basic model

The problem of source separation, appeared in 80's [3], [4], is often called 'blind separation of sources' because very weak hypotheses, either on source signals or on mixtures, are assumed.

In a large number of applications, the signal delivered by a sensor is an *unknown* superimposition of the various sources: this is the case for a microphone, an antenna or more generally any other sensor. In the simplest case, the output signals $x_i(t), (i = 1, \cdots, n)$ of a sensor array can be consider as instantaneous (memoryless) mixtures of m *unknown* (unobserved) source signals $s_j(t), (j = 1, \cdots, m)$:

$$x_i(t) = \sum_{j=1}^{m} a_{ij} s_j(t), \quad i = 1, \cdots, n \tag{1}$$

For sake of simplicity, assume that the number of sources is known and is equal to the number of sensors i.e. $m = n$ (the case $m \neq n$ will be discussed later). Equation (1) can be expressed in a vectorial form as:

$$\mathbf{x}(t) = \mathbf{A}\mathbf{s}(t) \tag{2}$$

where $\mathbf{x}(t) = [x_1(t), \cdots, x_n(t)]^T$ is the observation vector, $\mathbf{s}(t) = [s_1(t), \cdots, s_n(t)]^T$ is the unknown source vector and $\mathbf{A}$ is a square $n \times n$ *mixing matrix* with *unknown* scalar entries, a_{ij}. A source separation algorithm consists in estimating a $n \times n$ *separating matrix* $\mathbf{W} \approx \mathbf{A}^{-1}$ whose output:

$$\mathbf{y}(t) = \mathbf{W}\mathbf{x}(t) = \mathbf{W}\mathbf{A}\mathbf{s}(t) \tag{3}$$

should be an estimation of the vector $\mathbf{s}(t)$ of the sources: $\mathbf{y}(t) = \hat{\mathbf{s}}(t)$ (Fig. 1).

The following problem arises: how a *BSS* algorithm can estimate (recover) the original sources, $\mathbf{y}(t) = \hat{\mathbf{s}}(t)$, and the separation matrix, $\mathbf{W} \approx \mathbf{A}^{-1}$, from the observations $\mathbf{x}(t)$. The lack of any knowledge about mixture is compensated by the assumption of *statistical independence* between the source signals, $s_i(t)$. This seems a strong assumption but it is very realistic in this context. Independence can be expressed in terms of probability, but it also means simply that knowing $s_i(t)$ does not give information on $s_j(t)$, $j \neq i$ ($s_i(t)$, $s_j(t)$ arise from different physical sources). For example, two speech signals coming from two persons are statistically independent, and two different magnetic sources emit two independent magnetic fields. Hence, a *BSS* algorithm estimates $\mathbf{W}$ by optimization of an independence criterion for the estimated sources, $\mathbf{y}(t)$. In other words, the separation is achieved when the estimated sources become mutually statistically independent.

The independence criterion is based on the independence definition of the multivariate random variable $\mathbf{y} = [y_1, \cdots, y_n]^T$. The components y_i, $i = 1, \cdots, n$ of $\mathbf{y}$ are independent if the joint probability distribution $p_{\mathbf{y}}(\mathbf{u})$ is equal to the product of marginal probability distributions $p_{y_i}(u_i)$:

$$p_{\mathbf{y}}(\mathbf{u}) = \prod_{i=1}^{n} p_{y_i}(u_i) \tag{4}$$

Thus, the independence can be measured by the 'distance' between the joint probability distribution and the product of marginal probability distributions, such as done by the Kullback-Leibler divergence, also called mutual information:

$$I = \int p_{\mathbf{y}}(\mathbf{u}) log \frac{p_{\mathbf{y}}(\mathbf{u})}{\prod_{i=1}^{n} p_{yi}(u_i)} d\mathbf{u} \tag{5}$$

It can be easily shown that (5) is positive, and equal to zero if and only if (4) is satisfied. Then, (5) is a simple theoretical independence criterion whose minimization with respect to the $\mathbf{W}$ leads to output independence. Minimization of (5) requires the knowledge of the densities $p_{y_i}(u_i)$, which can be approximated by a Gram-Charlier expansion [9], [10] or directly estimated [11], [12].

Another approach is based on the characteristic functions of the random variables $y_i, i = 1, \cdots, n$. The *first characteristic function* is defined as the Fourier transform of the probability distribution $p_{y_i}(u_i)$:

$$\Phi_{y_i}(\omega) = \int_{-\infty}^{+\infty} e^{-jy\omega} p_{y_i}(u_i) du_i \tag{6}$$

and the *second characteristic function* as the logarithm of the first characteristic function:

$$\Psi_{y_i}(\omega) = log(\Phi_{y_i}(\omega)) \tag{7}$$

Applying (7) to the definition (4), the independence of two random variables y_i et y_j $(i \neq j)$ writes:

$$\Psi_{\mathbf{y}}(\omega) - \sum_{i=1}^{n} \Psi_{yi}(\omega) = 0 \tag{8}$$

By expanding (8) in Taylor series, the independence condition requires the zeroing of statistical quantities which are easily expressed by statistical moments, the so-called *cross-cumulants* [13], [9].

Let us note that the independence criterion, specific to *BSS* problem, is much more powerful than a decorrelation criterion, and generally involves the use of the high-order statistics (higher than 2) of the estimated sources [6], [13].

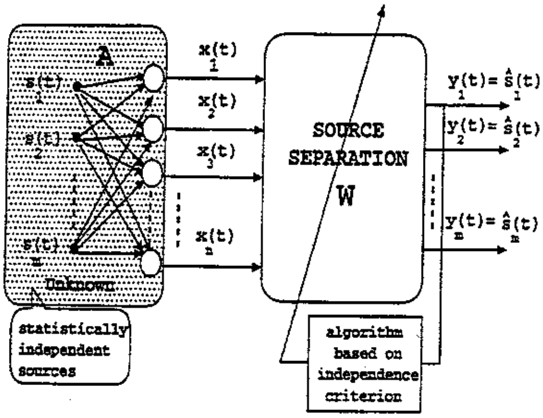

Fig. 1. Schematic diagram of the basic *BSS* model $(n = m)$.

There are several issues in the blind source separation problem. The main issue is the existence of two inherent indeterminacies in the solutions. In fact, the observed mixtures $x_i(t), i = 1, \cdots, n$ are not modified by scale changes and permutation:

$$x_i(t) = \sum_{j=1}^{m} a_{ij} s_j(t) = \sum_{j=1}^{m} \frac{a_{i\sigma(j)}}{c_{\sigma(j)}} (c_{\sigma(j)} s_{\sigma(j)}(t)) \tag{9}$$

where $c_{\sigma(j)}$ is a constant and $\sigma(.)$ is a permutation on $1, \cdots, n$. Therefore, the sources cannot be exactly estimated, but only up to a permutation and a scale factor:

$$\mathbf{y}(t) = \mathbf{PDs}(t) \tag{10}$$

where $\mathbf{D}$ is a $n \times n$ diagonal matrix with non-zero entries and $\mathbf{P}$ is a $n \times n$ permutation matrix. It means that $\mathbf{W}$ is not the inverse of $\mathbf{A}$ but verifies:

$$\mathbf{WA} = \mathbf{PD} \tag{11}$$

$$\mathbf{W} = \mathbf{PDA}^{-1} \tag{12}$$

Although the indeterminacy seems to be a severe limitation, in a great number of applications it is not essential if the relevant information about source signals is contained in their waveform shape. On the contrary, if the magnitude of source signals is needed, then a calibration is required.

Another issue is the implementation strategies of source separation algorithms. For instance, the estimation of the separation matrix $\mathbf{W}$ can be performed 'on-line' by an adaptive (e.g. neural-type) algorithm or 'off-line' by a batch algorithm. The choice depends on the application: in real-time applications, for example, an adaptive algorithm is required.

B. Extensions of the basic model

In practical *BSS* applications, the basic model (1) is often too simple or its assumptions are not realistic.

Various extensions of the basic model are discussed in this section.

• *More/less observations than sources* ($n \neq m$). In real-world applications the source number can be unknown and time-variable. However, many *BSS* algorithms are particularly efficient if the number of sources is equal to the number of sensors. There are two possible situations:

a) With more sensors than sources ($n > m$), a first step consists in estimating the source number m. Then, a whitening stage can transform the n observations into m uncorrelated observations, with the best signal to noise ratio. This problem has been intensivelly studied in signal processing and many solutions are available [14], [15]. A m-size source separation algorithm, located after the whitening stage, is then very efficient.

b) With less sensors than sources ($n < m$) the problem is especially problematic because the observations $\mathbf{x}(t)$ do not contain enough information for exactly separating all sources. The n most powerful are estimated, but with a distorsion due to the $m - n$ other sources.

• *Noisy observations.* Equation (1) corresponds to an ideal sensor output. In the realistic case, there is additive noise at each sensor output (electronic noise, for example):

$$x_i(t) = \sum_{j=1}^{m} a_{ij} s_j(t) + n_i(t), \quad i = 1, \cdots, n \qquad (13)$$

$$\mathbf{x}(t) = \mathbf{A}\mathbf{s}(t) + \mathbf{n}(t) \qquad (14)$$

Usually, the noise can be supposed uncorrelated with the observations. However, even if $\mathbf{W}$ can be perfectly estimated, there is always a remaining noise component, $\mathbf{W}\mathbf{n}(t)$, in the estimated sources:

$$\mathbf{y}(t) = \mathbf{W}\mathbf{x}(t) = \mathbf{W}\mathbf{A}\mathbf{s}(t) + \mathbf{W}\mathbf{n}(t) \qquad (15)$$

Experimental results confirm that additive noise decreases the source separation performance. However, if $n \gg m$, it is possible to improve the SNR by a preprocessing (projection in the signal subspace). Otherwise, noise reduction must be applied after the source separation stage.

• *Ill-conditionned mixture.* In an integrated sensor array application, the mixtures can be very similar (the mixing matrix is then ill-conditionned). The so-called *equivariant* source separation algorithms [5], [6] can overcome this problem. Another solution is to design sensor array which has a good spatial diversity, e.g. by choosing various geometry or orientation of sensors.

• *More complex model of mixtures.*

a) linear convolutive. In more realistic model, linear filtering between sources and sensors must be taken in account:

$$\mathbf{x}(t) = \mathbf{A}(t) * \mathbf{s}(t) \qquad (16)$$

where $\mathbf{A}(t)$ is a matrix whose entries are filters and $*$ denotes convolution. For instance, assuming FIR filters of order p, (16) becomes [7]:

$$x_i(t) = \sum_{j=1}^{m} \sum_{k=0}^{p-1} a_{ij}(k) s_j(t-k), \quad i = 1, \cdots, n \qquad (17)$$

b) nonlinear. The more general problem of nonlinear mixtures has been recently adressed, and efficient algorithms have been proposed [8], [12] for the so-called post non-linear mixtures:

$$x_i(t) = f_i\left(\sum_{j=1}^{m} a_{ij} s_j(t)\right) \qquad (18)$$

where $f_i(.)$ is any unknown inversible non-linear function.

• *Use of prior information.* Any additional information on the sources can be often used to improve the separation results or to simplify the algorithms [16].

C. BSS aproach to low-cost high-performance sensor microsystems

Source separation approach appears as an attractive method for designed smart sensor array, able to increase spatial selectivity and to cancel the cross-sensitivity. Up to now, this class of algorithms has been mainly used in telecomunications, speech processing, biomedical signal processing applications. For the first time, we have applied it in the case of integrated sensor array (to design low cost high performance Hall-type silicon sensors). The analytical model of Hall-device cross-sensitivity is presented in the following section. This study is necessary to chose the suited model of mixtures.

IV. HALL-DEVICES B-T CROSS-SENSITIVITY

The sensor array used in our application is based essentially on silicon Hall-plates with various geometries. The principle of a Hall-plate sensor is given in Fig. 2: when the device is placed in a magnetic field, B, perpendicular to its surface, a Hall voltage, V_{Hall} is sensed between the lateral contacts (V_{H+}, V_{H-}).

The Hall device sensitivity ($i.e. S = dV_{Hall}/dB$) varies with the temperature and/or stress *(cross-sensitivity)*, thereby reducing measurement accuracy [17]. Figure 2 shows typical Hall voltage (V_{Hall}) as a function of the magnetic field, B, with the temperature, T, as a parameter. Systematic measurements are made on silicon n-type Hall plate with different geometry and on MAFGFETs (both CMOS compatible) and it is found that B and T influences on V_{Hall} are well modeled by a conventional simple relation [1]:

$$\begin{aligned} V_{Hall} &= \mu_n(T) G \frac{Z}{L} V B + V_{off}(T) \qquad (19) \\ &= (\mu_{n0} T_0^{\gamma} G \frac{Z}{L} V) B T^{-\gamma} + V_{off}(T) \\ &= k B T^{-\gamma} + V_{off}(T) \end{aligned}$$

where V_{off} is the offset voltage, Z and L are the Hall plate width and length, respectively, μ_{no} is the carrier mobility at $T_0 = 273K$ and V is the applied voltage. It is experimentally verified that in deduced sensitivity, $S = kT^{-\gamma}$, the γ coefficient mirrors mainly the temperature dependence of carrier mobility in doped silicon and it is less influenced by sensor geometry. Note that for small temperature variations (ΔT up to 20-40K) a linear approximation can be assumed: $V_{Hall} \propto (\alpha - \beta T)$, where coefficients α and β are determined for a given range of temperature. With this hypothesis, for a given sensor, differenciating equation (19) and neglecting offset contribution gives:

$$\begin{aligned} dV_{Hall} &= (-\beta k B)dT + k(\alpha - \beta T)dB \qquad (20) \\ &= (-\beta k B^* \frac{dT}{dV_{Hall}}|_{B^*})v_{HT} \\ &\quad +((\alpha - \beta T^*)k \frac{dB}{dV_{Hall}}|_T^*)v_{HB} \end{aligned}$$

where v_{HT}, v_{HB} are the equivalent induced Hall voltage ('signals') if T and B vary, respectively. The equation (20) is similar to the source separation data model (1) and for a Hall sensor array, it can be written as:

$$v_i = a_{i1} v_{HT} + a_{i2} v_{HB}, \; i = 1, \cdots, n \qquad (21)$$

where the a_{i1} and a_{i2} are the cross-sensitivity mixing coefficients. It means that the cross-sensitivity can be modelled by instantaneous linear mixtures, and that source separation algorithms should be efficient to cancel it.

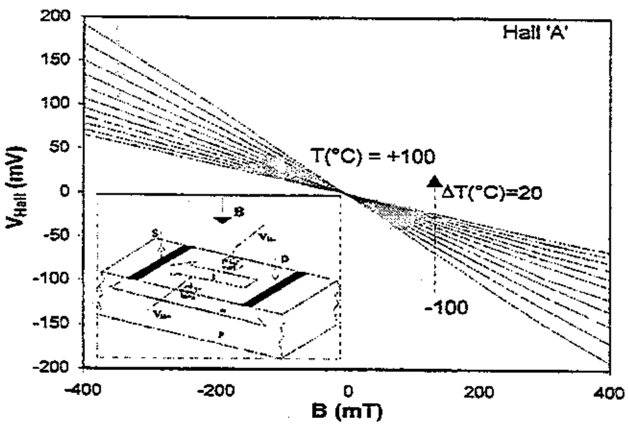

Fig. 2. Hall voltage, V_{Hall}, as a function of the magnetic field B, with the temperature as a parameter, for a conventional Hall plate. Inset: Hall plate schematics

V. SIMULATION RESULTS

The microsystem architecture which is currently designed is given in Fig. 4. Its performance was validated by the simulations depicted in the following.

After individual sensor behavior evaluations as functions of the magnetic field (up to $400mT$) and temperature ($-100°C$ up to $+100°C$), sensors with different geometry were selected (to avoid a ill-conditionned mixture).

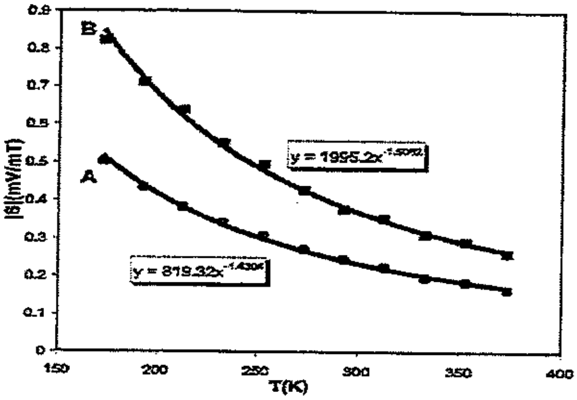

Fig. 3. Measured and simulated sensitivity, $S = dV_{Hdiff}/dB$, for two different geometry magnetic sensors (Hall-plates 'A' and 'B') as a function of temperature

In the simulations, we consider a sensor array with six Hall-plate, and three independent sources: a temperature source $T(t)$, slowly varying, and two magnetic sources, $B1(t)$ and $B2(t)$ (coming, for example, from turning machines) (Fig. 5). Using the $B-T$ cross-sensitivity model (21), we simulate the mixed signals, taking also into account the additive noise, mirroring offset and sensor electronic noise (Fig. 6).

Of course, the source separation algorithm processes only the mixed signals that appear on the sensor outputs.

Simulations were running on a SUN SPARC station, but requires a weak computation power. After the source number was estimated, the sources are separated on-line after a short convergence time (a few ms), with a remaining crosstalk of about $-25dB$ to $-30dB$. Figure 7 shows, as explain in section III.A, that sources are estimated up to a scale factor and a permutation.

VI. HARDWARE IMPLEMENTATION ISSUES

It is obvious that the performance of a source separation algorithm, running on a computer (32 bits, floating point computations) can be substantially different compared to those of an IC which performs the same calculations with a limited accuracy.

The problems arrising when a hardware implementation is desired are the following:

• *the technology choice (analog/digital VLSI).* Source separation algorithms have been successfully implemented in analog CMOS VLSI [18], [19]. This can be a very attractive approach for 'integrated smart sensors' since the corresponding sensor can be designed and fabricated using the same technology as for the source separation IC. The main drawback is the lack of flexibility (the algorithm is suited to a unique application) which is required in many real applications for efficient imple-

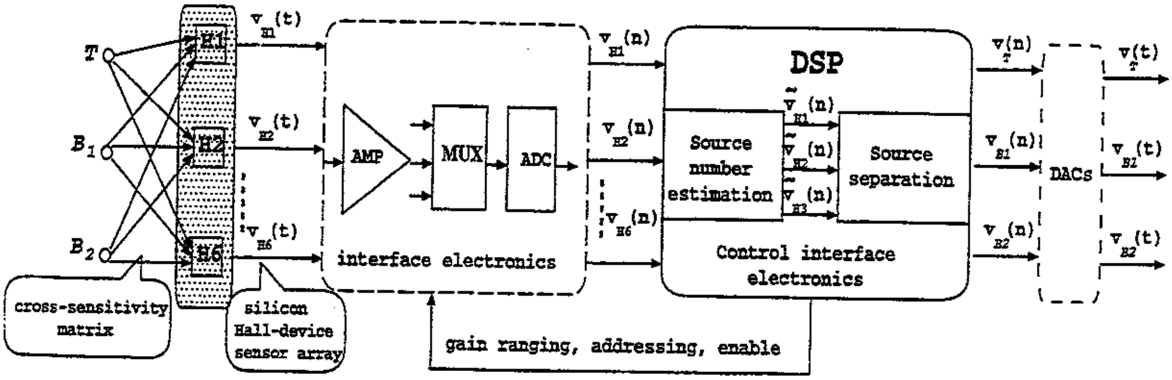

Fig. 4. Schematic architecture of the magnetic sensors microsystem

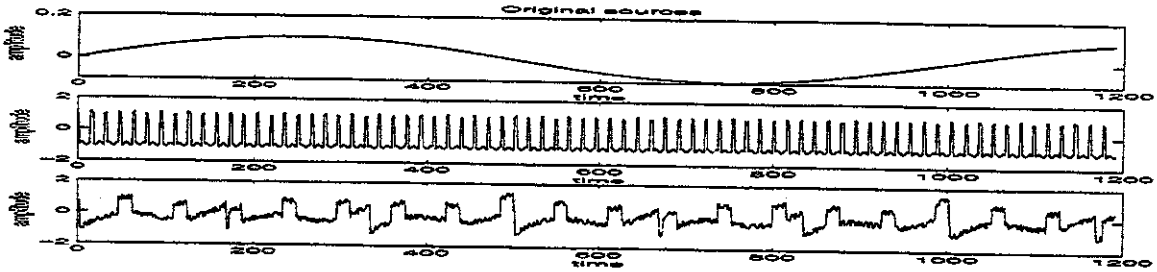

Fig. 5. The original sources: induced Hall-voltages, $v_{HT}(t), v_{HB1}(t), v_{HB2}(t)$, due to T, B_1, B_2 variations

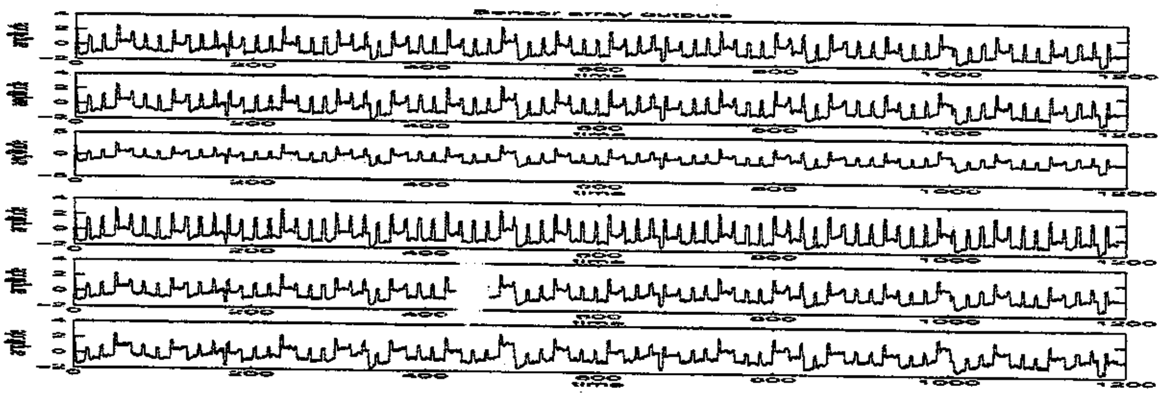

Fig. 6. The mixed sources, $v_{Hi}(t)(i = 1, \cdots, 6)$ (sensor outputs)

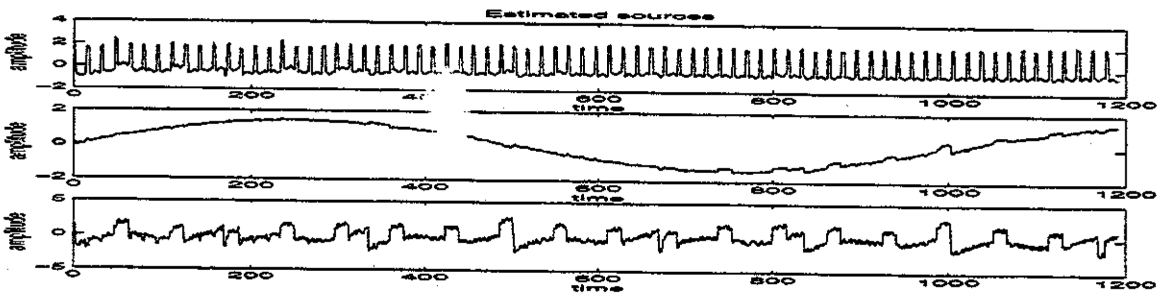

Fig. 7. The estimated sources (up to a permutation and a scalar factor)

mentation of source separation algorithms.

• *the flexibility* can be obtained by the digital implementation (DSP) and it is generally suitable in many practical cases, for instance:

a) more complex algorithms (e.g. source number unknown, a lot of sources to be estimated)

b) various algorithms which must be implemented and adapted for different applications.

• *the cost* of the microsystem is often an important criterion in the design of its architecture. The study of the algorithm performance in limited accuracy becomes essential for this purpose. For example, if the DSP solution is chosen, we need to determine the minimal accuracy required (e.g number of bits for data quantization, DSP word-length, fixed- or floating-point computations) for good performance of the microsystem.

Results demonstrate that the learning of the separating matrix **W** needs a good accuracy (16 bits fixed-point). Signal quantization can be performed with a lower precision: 8-12 bits ADC can be used.

VII. CONCLUSIONS

The feasibility of a new type of smart microsystem, based on the combination of a sensor array and a source separation signal processing, is demonstrated.

The microsystem is able to cancel the cross-sensitivity and the crosstalk and the principle can be applied to any multi-sensing application.

In the case of silicon magnetic field (Hall) sensors, which are well known for their $B-T$ cross-sensitivity, we proved the efficiency of this approach to cancel both cross-sensitivity and crosstalk using a low-cost sensor array.

Currently, we design a complete prototype, as depicted in Fig. 4, in which mixtures will be done directly by the sensor, instead to be simulated.

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