Tunnel Magnetoresistive Sensors based Current Transducer with Adaptive Blind Source Separation

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Abstract

In this paper, we propose a new approach for designing a high performance and low-cost sensor array based current transducer. This is based on the use of tunnel magnetoresistive sensor array and adaptive blind source separation method. Such a sensor array is able to cancel magnetic interference from nearby current carrying conductors by giving a near perfect estimation and separation of the unknown source signals. Experiment using a hardware prototype based on an analog interface and a DSP for enhancing flexibility was used. The result obtained with the used of Tunnel Magnetoresistive sensor array is presented in this paper.

Keyword: *Adaptive blind source separation, Interference cancellation, Sensor array, Tunnel Magnetoresistive sensor.*

I. INTRODUCTION

Magnetic sensors can be used to measure electric current by sensing the magnetic field near the current under measurement. However, a means is therefore required to differentiate between useful fields and interference fields that are created by those conductors near the current under measurement and other environmental fields.

Interference fields may reduce the accuracy of a contactless current transducer based on magnetic field measurement detected by a single magnetic sensor. This therefore makes it impossible for a single magnetic sensor to differentiate between the field generated by the current under measurement and other external fields.

In [1] cases of magnetic sensor circular arrays are presented. The sensing elements are assembled on a circuit around the conductor and in other to achieve a reduction in interference; an approximation of the Ampere's circuital law is performed giving the sum of the sensor signal output.

In a real-world application of signal processing, especially in communication and biomedicine, the problem of interference cancellation is very important[2] Interference cancellation is a major subject of wide interest in physical and communication systems. Many techniques have been suggested in the literature for interference reduction. Signal processing techniques used for interference reduction include; bandpass filtering, Fast Fourier Transform, autocorrelation, adaptive filtering, Kalman filtering and Singular Value Decomposition (SVD.[3]

This paper presents a new technique for interference cancellation based on sensor array with the used of adaptive blind source separation. Blind source separation was initially used in human brain but has now become an active research area both in statistical signal processing and unsupervised neutral learning [4][5]. The main objective of blind source separation (BSS) consists in recovering unobserved signals or 'sources' from two or more observed mixtures which are the outputs of an array of sensors without knowing the mixing coefficients. Generally, the observations are obtained at the output of a set of sensors, each sensor receiving a different combination of the 'source signals'. The term 'blind' stresses the fact that, the source signals are unknown and no information is available about the mixture.

[6] Presents theoretical results and practical algorithms on blind source separation. So far as there are at least many sensors as sources, the blind source separation algorithm is capable of estimating simultaneously a number of unknown sources from observed mixture. In using sensor array, blind source separation algorithm presents better results in interference cancellation.

This paper presents a new technique for interference cancellation based on sensor array with the used of adaptive blind source separation algorithm.

II. BASIC PRINCIPLES OF BLIND SOURCE SEPARATION

In many sensor applications, the output signal delivered by a sensor is an unknown superimposition of the various input sources; this is the case for a sensor array of a tunnel magnetoresistive sensors. Sensor array can simply be express in the form $x_i(k), (i = 1, \dots, p)$ and can be considered as a linear instantaneous mixture of n unknown source signals $s_j, (j = 1, \dots, n)$;

$x_i(k) = \sum_{j=1}^{p} a_{ij}\, s_i(k)$

(1)

Given that the number of sources are unknown and are less than the number of sensors $n < p$, then equation *(1)* can be written in the form;

$x(k) = As(k)$

(2)

Where $x(k) = [x_1(k), \dots, x_p(k)]^T$ is the observation vector, $s(k) = [s_1(k), \dots, s_n(k)]^T$ is the unknown source vector and *A(.)* denotes the mixing matrix whose scalar entries a_{ij} are unknown. A blind source separation algorithm main idea is to estimate a transform *B(.)* which inverses the mixture *A(.)* and without extra effort provides estimates of the unknown sources.

However, without other assumptions, this problem cannot be solved. Basically, it is important to have priors information about the nature of the mixtures, it is also very necessary to choose a separation transform *B(.)* suitable to the mixture transform *A(.)*[7].

$y(k) = Bx(k) = BAx(k)$

(3)

Should be an estimation of the vector *s(k)* of

$y(k) = \hat{s}(k)$

(4)

Another major challenge of using blind source separation is that neither *s(k)* nor *A* is available in the expression; $x(k) = As(k)$. However, the challenge is overcome using the assumption that the source signals $s_i(k)$ are statistically independent. Though a strong assumption, it is realistic in this context. Probability can be used to express statistical independence. It also means that knowing the independence of the source signal $s_i(k)$ does not necessarily give information on $s_j(k), j \neq i, (s_i(k), s_j(k))$

Two signals generated by two independent current-carrying conductors are considered statistically independent and that two different magnetic sources will emit two independent magnetic fields. A Blind Source Separation algorithm estimates *B* by the optimization of an independent criterion for *y(k).* Separation is therefore achievable when the components of *y(k)* become mutually statistically independent as illustrated in fig. 1.

Given that $y(k) = Bx(k)$, and assuming that the PDF of *u* is $p_y(u)$ and every source's PDF is $p_{yi}(y_i)$ then, the Kullback-Leibler (KL) divergence between $p_y(u)$ and $\prod_{i=1}^{n} p_{yi}(y_i)$ can be used as the measure of independence between each source.

Hence;

$I = \int p_y(u) \log\left[\frac{p_y(u)}{\prod_{i=1}^{n} p_{yi}(y_i)}\right] du$

(5)

Obviously, if and only if $p_y(u) = \prod_{i=1}^{n} p_{yi}(y_i)$, then, the mutual information is zero and every source is statistically independent.

Equation (5) is a theoretical independence criterion whose minimization with respect to the *B* leads to output

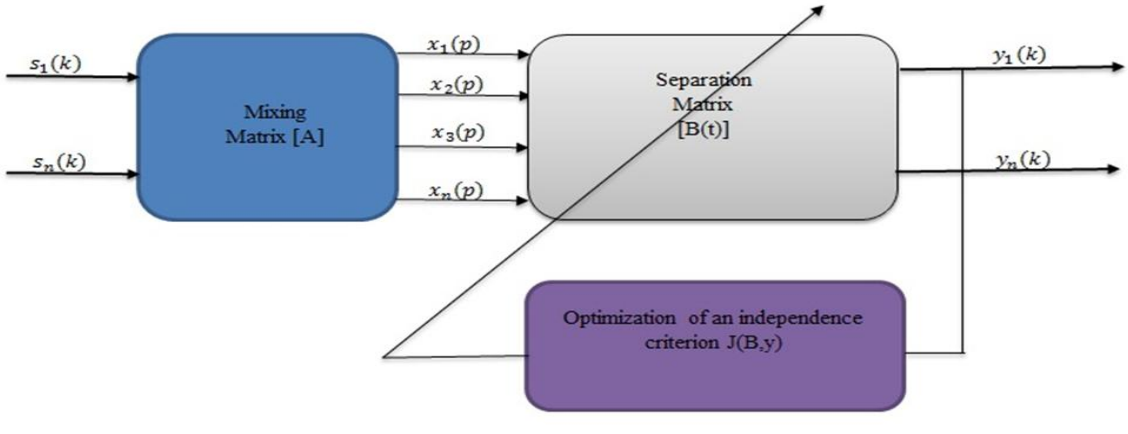

Fig. 1 Illustration of Adaptive Blind Source Separation

Equation (5) is a theoretical independence criterion whose minimization with respect to the *B* leads to output

Independence. Minimization of equation (5) requires the knowledge of the densities $p_{yi}(u_i)$ which can be approximated by a Gram-Charlier expansion as stated in[8][9].

Let us note that decorrelation criterion can also be used, however, the independence criterion specific to blind source separation problem is more powerful and generally involves the use of high-order statistics (HOS) of the estimated sources.[10] [11]

Blind source separation problems have many issues to deal with; however, the main issue is the existence of two inherent indeterminacies in the solution. The observed mixtures $x_i(k), i = 1, \dots, p$ is not modified by scale changes and permutation.

$x_i(k) = \sum_{j=1}^{n} a_{ij} s_i(k) = \sum_{j=1}^{n} \frac{a_{i\varphi}(j)}{c_{\varphi}(j)} (c_{\varphi}(j) s_{\varphi}(k))$

(6)

Where $c_{\varphi}(j)$ is a constant and $\varphi(.)$ is a permutation on $i, \dots, n$. Therefore, the sources cannot be exactly estimated but only up to a permutation and a scale factor.

$$y(k) = PDs(k) \quad (7)$$

Where *P* is a *n x n* permutation matrix and *D* is a *n x n* diagonal matrix with non-zero entries.

Even though the indeterminacy seems to be a limitation, in many applications, it is not important if the relevant information about the 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 major issue is the implementation techniques of source separation algorithms. For instance, the estimation of the separation matrix *B* can be performed by an adaptive neutral-type algorithm or by a batch algorithm. However, in a real-time application an adaptive algorithm is ideal. Adaptive blind source separation algorithm can be implemented using recurrent or feed-forward neutral networks[12].

III. TMR SENSOR OUTPUT AS MIXTURE FOR BLIND SOURCE SEPARATION

Blind source separation technique is a very attractive method for the design of sensor array. It is able to increase interference cancellation and spatial selectivity. Up to now this class of algorithms are mostly utilized in speech processing, biomedical signal processing and telecommunications applications.

TMR sensors have shown to be attractive in nearly all areas of magnetic sensors. They have proven to provide reliable data with high accuracy and significantly improved output signal compared to AMR and GMR sensors.

TMR is designed to be sensitive to magnetic fields perpendicular to its surface. At a constant current flow, the TMR sensor converts the magnetic field into voltage.

In real-world applications, the magnetic field can result from various independent sources; both interested sources and other unwanted sources, thus TMR sensor output is a complex function of various magnetic field sources inputs which can be expressed as;

$$V_{out} = f(B_1, \dots, B_m) + V_{offset}$$

(8)

Where V_{offset} is the sensor offset voltage

Assuming that we want to select the magnetic source of interest which is the sensor output, the blind source separation processing is a good technique to this formulated problem which does not require reference signal.

A TMR sensor response model in the form needed for adaptive blind source separation results by considering the variations of the B_i $i = 1, \dots, p$ sensor outputs. The output voltage of a TMR sensor is expressed as;

$$V_{out} = KBsin\theta$$

(9)

Where *K* is the sensor sensitivity which is equal for all the sensors used for this project, *B* is the magnetic field density and θ is the angle of incidence of the magnetic field. The spatial diversity of various magnetic field sources in the sensor environment is a well-suited feature for blind source separation technique. For a given sensor and differentiating at first order;

$$dV_{out} = K \frac{B_n sin\theta_n}{dV_{out}} \Big| B_i^*, i = n \;\; V_{out} B_k$$
$$+, \dots + K \frac{B_n sin\theta_n}{dV_{out}} \Big| B_i^*, i = n \;\; V_{out} B_k$$

(10)

Where $V_{out} B_1, \dots, V_{out} B_k$ are the equivalent induced sensor voltage by k independent variable magnetic sources, $B_1, \dots, B_k$. For a sensor array, a system of linear equations is obtained.

IV. BLIND SOURCE SEPARATION MAKE-UP

[13] presents a simple blind source separation algorithm implemented in analog VLSI. It is a very good approach for integrated smart sensors as far as the corresponding sensor array can be design and fabricated using the same technology.

The work in this paper is done on a DSP based sensor system architecture to ensure high flexibility and low cost.

For real-world applications and quick implementation of different algorithm in such a system, the software elements become dominant.

The originality of our work lies in the fact that the number of sources in the sensor environment is considered unknown and also time-varying. The sensor output is also considered to be mixed with noise.

The condition we however took into consideration is that; we have more sensors than the number of sources and that the number of sources is adaptively estimated before separation is done. This ensures fast processing for real-time source separation.

In blind source separation process, after the source signal waveforms separation, a calibration is needed for the amplitude estimation which can be done using software polynomial calibration approach or continuous calibration approach proposed in [14][15]

V. TMR SENSOR ARRAY PROCESSING

In this paper, our main aim is to separate the source signals in the real noisy sensor environment and to identify the signal of interest. In (10) the output voltage of a TMR sensors array is presented as;

$$V_{out}(k) = AV_{outB}(k) + n(k)$$

(11)

Where $V_{out}(k) = [V_{out}(k), \dots, V_{outp}(k)]^T$ is the vector of the observed voltage at the sensor array output,
$V_{outB}(k) = [V_{outB1}(k), \dots, V_{outBn}(k)]^T$ is the vector of the induced voltages by n magnetic field sources and $n(k) = [n_1(k), \dots, n_p(k)]^T$ is the vector of the corresponding additive electronic noise which can be assumed as Gaussian and not correlated with $V_{outB}(k)$

VI. SOURCE SEPARATION

Before the adaptive blind source separation algorithm can be implemented in real-time situation to produce good and acceptable results, several factors must be considered, which include;
The independence of source signals, conditioning of the mixing matrix, the nature of source (stationary and non-stationary source) and the optimization procedure for estimating the separation matrix *B*.
The source signals should be statistically independent. And [16] outline how to increase the flexibility of the algorithm by using on-line monitoring of the corresponding adaptation.
Another factor of concern is the mixing matrix. From [10][17] an algorithm without equivariant properties may fail to separate ill-conditioned mixtures.
The stationarity of the source is another factor since this makes the situation difficult. One solution for efficient tracking is an adaptive step-size. [18][10][17] Present the optimization procedure for estimating the separation matrix *B*.
For the practical implementation of the adaptive blind source separation algorithm, it requires that the algorithm be made flexible to ensure that it is able to adapt to real-world situations. However, making the algorithm flexible increases its computational complexity. As a result, ways of simplifying the algorithm implementation without affecting its performance can be use. Such could be the use of priori information on the data application model.

Fig. 2 shows the schematic architecture of the transducer which was used for the experiment. Its performance was validated by way of simulation which was performed using the ANSYS Maxwell and also on MATLAB.
The individual sensor behaviour was evaluated as a function of the magnetic field after which the average magnetic field of the sensors was calculated using ANSYS Maxwell.
In our simulation, we used four tunnel magnetoresistive (TMR) forming a sensor array and two magnetic sources;
Fig. 3 shows the original signals for two magnetic field sources $B_1(k)$ and $B_2(k)$ coming from two current carrying conductors with a minimum of 500A and 1000A.
Fig. 4 shows the simulation of the mixed signals from the sensors taking into account additive noise such as sensor electronic noise.

The source separation was performed with the algorithm implemented in adaptive blind source separation. The algorithm processes only the mixed signals that appear on the sensor output. After the source number estimation, the source separation was then on-line. Fig. 5 shows that the sources are estimated up to a scale factor and a permutation.
This algorithm shows good performance for both stationary and non-stationary sources. Though the algorithm gave good results however, for integrated smart sensors arrays, the output signals can be very ill-conditioned due to the proximity of the sensors. In avoiding the ill-conditioned nature of sensors output signals, we design our sensor array in a circular form and this produced very good results.

In implementing adaptive blind source separation algorithm in fixed point using sensor array, care must be taken to avoid overflow. Due to the blind approach nature of the algorithm, some difficulties may be encountered. It was realized that the equivariant algorithms are more difficult to scale because of a particular structure.

VII. SIMULATION RESULTS

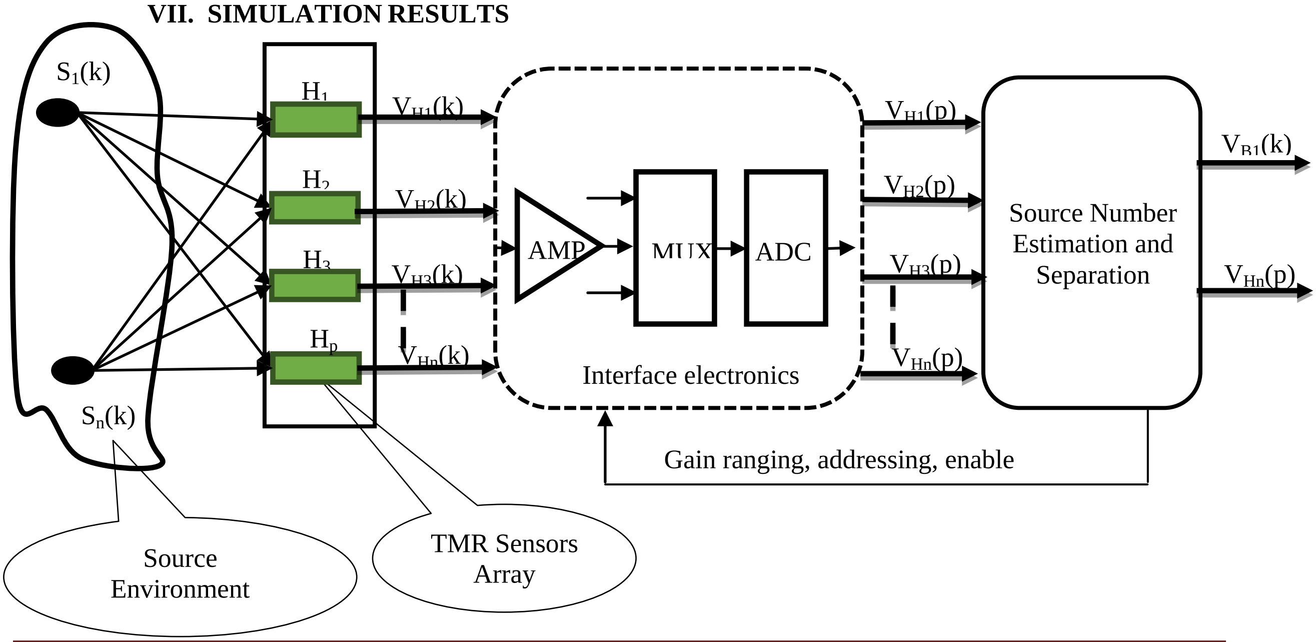

Fig. 2 Schematic Architecture of Tunnel Magneto resistive (TMR) Sensor System with Adaptive Source Estimation and Separation Processing.

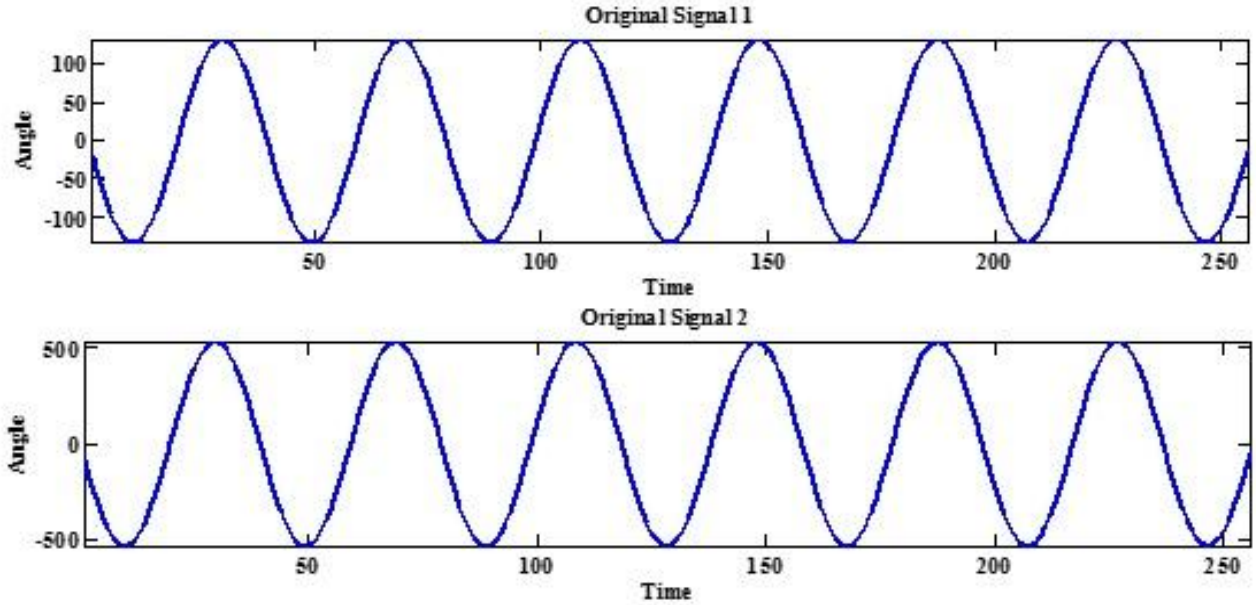

Fig. 3 Original Signals for two Independent Magnetic Field Sources $B_1(k)$ and $B_2(k)$

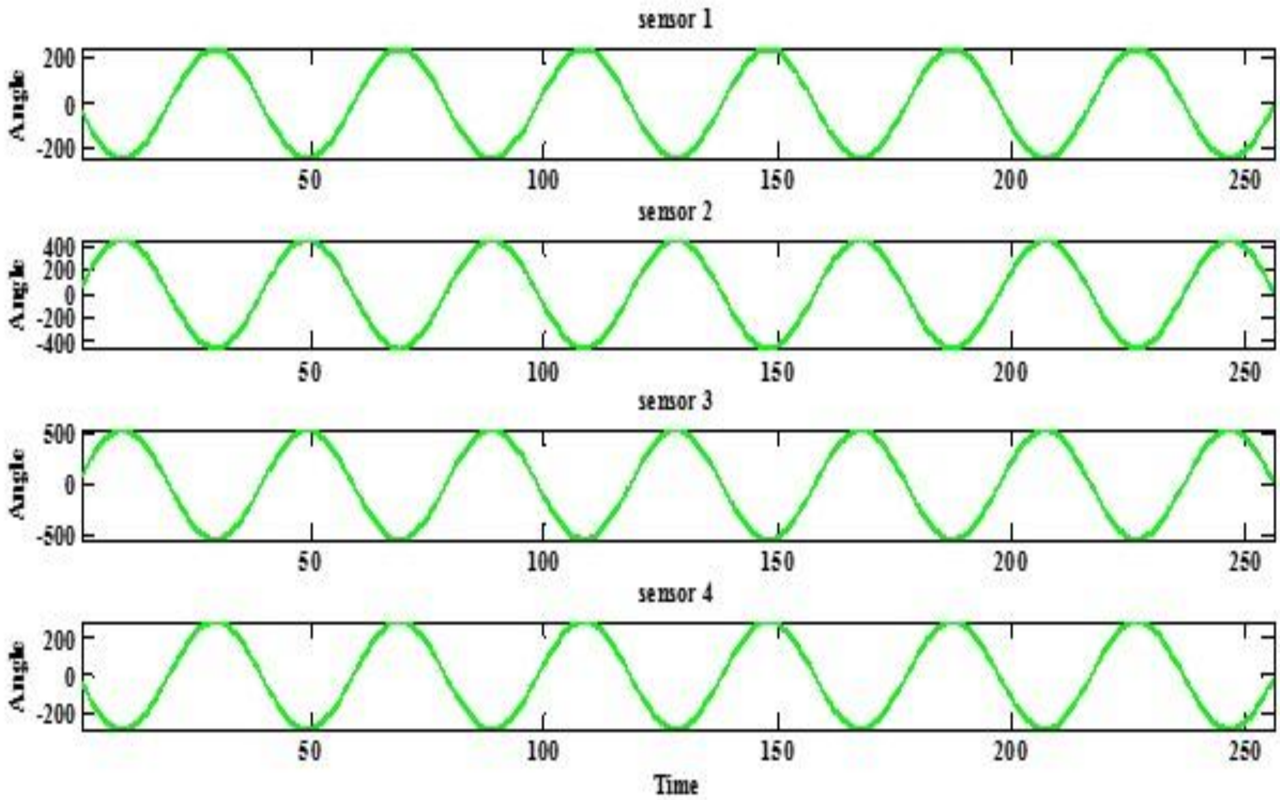

Fig. 4 Mixed Source Signals, $V_{out}(k)$ (i=1, …, 4) Sensor Outputs.

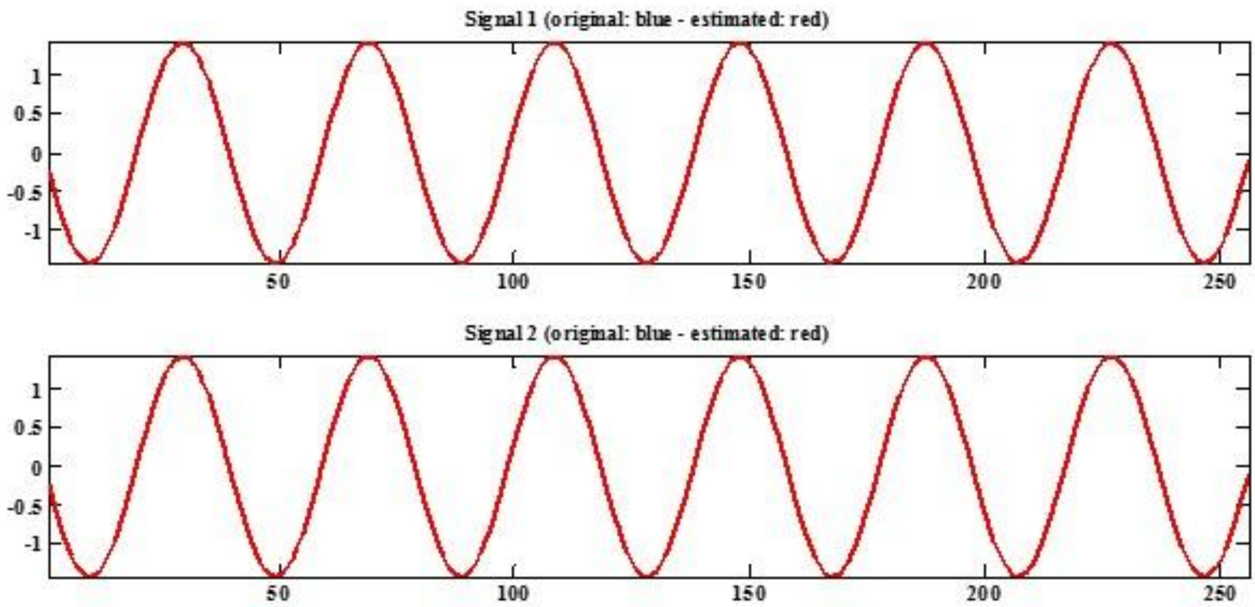

Fig. 5 Estimated Source Signals (Up to Permutation and a Scale Factor)

CONCLUSION

We have successfully proposed and demonstrated a cost effective and robust solution for unknown source estimation and separation using adaptive blind source separation. Our method estimates the unknown source as well as the separation of unknown current - carrying sources with TMR sensor array with the number of sensors more than the number of sources. The developed algorithm first estimates the number of sources and carry out source separation accurately. We tested the proposed sensor design and algorithm by means of numerical simulations and based on MATLAB and laboratory experiment. After testing this method on a number of scenarios, the error for source estimation and separation remains less than 1%. Under experimental situation when compared with the numerical simulation, the error remains same as a result of the small incremental step size used in the algorithm. However, the error could increase slightly if there is an increase in electronic noise in the sensing system.

REFERENCE

[1] R. Weiss, R. Makuch, A. Itzke, and R. Weigel, “Crosstalk in Circular Arrays of Magnetic Sensors for Current Measurement,” IEEE Trans. Ind. Electron., vol. 64, no. 6, pp. 4903–4909, 2017.

[2] F. Fir, F. Iir, T. Fir, I. Transactions, and S. Processing, “8 . Adaptive Filters.”

[3] S. Vorobyov and A. Cichocki, “Blind noise reduction for multisensory signals using ICA and subspace filtering, with application to EEG analysis,” Biol. Cybern., 2002.

[4] J. Schmidhuber, “Deep Learning in neural networks: An overview,” Neural Networks, vol. 61. pp. 85–117, 2015.

[5] Z. Ghahramani, “Unsupervised Learning BT - Advanced Lectures on Machine Learning,” Adv. Lect. Mach. Learn., vol. 3176, no. Chapter 5, pp. 72–112, 2004.

[6] S. Choi, A. Cichocki, H.-M. Park, and S.-Y. Lee, “Blind source separation and independent component analysis: A Review,” Neurocomputing, vol. 6, no. 1, pp. 1–57, 2005.

[7] C. Jutten and M. Babaie-Zadeh, “Source separation: Principles, current advances and applications,” Notes, pp. 1–10, 1997.

[8] J. L. Lacoume, M. Gaeta, and W. Kofman, “Source separation using higher order statistics,” J. Atmos. Terr. Phys., vol. 54, no. 10, pp. 1217–1226, 1992.

[9] S. Fiori, “Entropy optimization by the PFANN network: application to blind source separation.,” Network, vol. 10, no. 2, pp. 171–86, 1999.

[10] S. Amari, A. Cichocki, and H. Yang, “A new learning algorithm for blind signal separation,” Adv. Neural Inf. Process. Syst., vol. 8, pp. 757–763, 1996.

[11] P. Comon, “Independent component analysis, A new concept?,” Signal Processing, vol. 36, no. 3, pp. 287–314, 1994.

[12] S. Amari and A. Cichocki, “Adaptive blind signal processing-neural network approaches,” Proc. IEEE, vol. 86, no. 10, pp. 2026–2048, 1998.

[13] M. H. Chowdhury, “Noise separation in analog integrated circuits using blind source separation,” 2007 IEEE Int. Conf. Electro/Information Technol., pp. 16–20, 2007.

[14] M. Možek, D. Vrtačnik, D. Resnik, U. Aljančič, S. Penič, and S. Amon, “Digital self-learning calibration system for smart sensors,” Sensors Actuators, A Phys., vol. 141, no. 1, pp. 101–108, 2008.

[15] P. NEWMAN, “CONTINUOUS CALIBRATION OF MARINE SEISMIC SOURCES,” Geophys. Prospect., vol. 33, no. 2, pp. 224–232, 1985.

[16] S. C. Douglas, A. Cichocki, and S.-I. Amari, “Multichannel Blind Separation and Deconvolution of Sources with Arbitrary Distributions,” in Proc. IEEE Workshop on Neural Networks for Signal Processing (NNSP’97), 1997, pp. 436–445.

[17] J. F. Cardoso and B. H. Laheld, “Equivariant adaptive source separation,” IEEE Trans. Signal Process., vol. 44, no. 12, pp. 3017–3030, 1996.

[18] N. Murata, M. Kawanabe, A. Ziehe, K. R. Muller, and S. Amari, “On-line learning in changing environments with applications in supervised and unsupervised learning,” Neural Netw, vol. 15, no. 4–6, pp. 743–760, 2002.