Extraction of Sensory part of Ulnar Nerve Signal Using Blind Source Separation Method

Alireza Kashaninia[1], S. Nooreddin Jafari [2]

[1] Assistant Professor in Electrical Engineering, Islamic Azad University, Central Tehran Branch (IAUCTB), Advanced Bionic Systems (ABS) lab, Tehran, Iran. Email: a_kashaninia@sbu.ac.ir

[2] M. Sc Degree in Electrical Engineering, Department of electrical engineering, Islamic Azad University, Langaroud branch, Guilan, Iran. Email: jafari@iaul.ac.ir

Abstract

A recorded nerve signal via an electrode is composed of many evokes or action potentials, (originated from individual axons) which may be considered as different initial sources. Recovering these primitive sources in its turn may lead us to the anatomic originations of a nerve signal which will give us outstanding foresights in neural rehabilitations. Accordingly, clinical interests may be raised on extraction of sensory and motor components of the nerve signals in neural injuries. One example is to extract sensory fraction in sacral nerve to sense the bladder filling up in paraplegic or quadriplegic people [3]. Blind Source Separation (BSS) methods seem good solutions for extraction of the initial sources which are contributing in recorded mixed sources. Considering the nerve signal as a superposition of many axonal or fascicular signals, we have encouraged to try BSS methods to see whether it can recover the sensory and motor sources of a recorded nerve signal. Accordingly, both PCA and ICA techniques were examined in a case study (human left arm), in which the response of the ADM muscle to the Ulnar nerve stimulation were recorded in two points. The corresponded sensory signal was recorded on the pinkie at the same time (all recordings were done via surface electrodes). It was shown that ICA (supremely better than PCA) was able to separate initial sources (ADM recorded signals) into two signals so that one of them was most similar to the sensory (Pinkie) signal. The level of similarity was quantified via correlation analysis. As the result, it is concluded that ICA is capable of extracting Sensory and Motor signals in PNS.

Keywords: PNS[1], ENG[2], surface electrode, Ulnar nerve signals, sensory signal, motor signal, BSS[3], PCA[4], ICA[5], Correlation Analysis.

[1] - Peripheral Nervous System
[2] - Electro Neurography
[3] - Blind Source Separation
[4] - Principal Components Analysis
[5] - Independent Components Analysis

1. Introduction

Peripheral nerve ganglia are the axonal extension of the somas located in CNS[6] (spinal cord). A signal recorded from a nerve via a typical electrode is originated from many action potentials (evokes) which are generated in individual neurons and carried over the corresponded axons which are bundled with each other to compose the nerve fascicles and the nerve. So, the nerve signal may be considered as a superposition of axonal or fascicular signals. The nerve signal is composed of spontaneous spikes, which are occurring randomly, due to the random activation of the axons. But, when a nerve is stimulated externally, many axons will respond simultaneously so that they generate a smoother wave shape (rather than what is seen in spontaneous response) in lower frequency band. In this paper, the stimulated response of a nerve is studied.

The signal, which is recorded at the vicinity of a nerve, is called Electroneurogram-ENG. It may be recorded via a variety of electrodes in different applications (from surface to penetrating epineural electrodes). Some examples are cuff, FINE[7] and intrafascicular electrodes (e.g. MEA[8]) [1-3, 14, 15, 19-21]. Cuff electrode records the superposition of the fascicle signals at the surface of the nerve. MEA, on the other hand, penetrates the nerve tissue, records fascicle signals with higher resolution, but causes more damages to the nerve tissue. Surface (skin) electrodes record both ENG and EMG[9] (myofibrils activity in response to ENG) signals which are filtered by the transbody tissues such as muscle boy, fats and skin. The results of employing such surface signals (which are used in this study) may be valid as we are focusing on extracting primitive sources of the ENG signals.

Extraction of sensory and motor sources of the neural signal may be advantageous for instance, in neural injury people who need stimulation of motor units in their limbs, bladder and so on, in response to sensory signals (such as discharging the bladder when its filling up is sensed via recording the sacral nerve).

Many efforts on functional recovery and rehabilitation of a nerve, after occurrence of a lesion in its path, have been reported, employing different strategies (Tessler, 1991 [4]; Schnell and Schwab, 1993 [5]; Schwab et al., 1993 [6]; Faden and Salzman, 1994 [7]; Reier et al., 1994 [8]; Li et al., 1997 [9]). These strategies have focused on 3 ways: 1) grafting an auxiliary nerve to bypass the lesion (within a specific period of the time after the injury [10]); 2) transplanting the neuroglia tissues (e.g. Schwann cells [11]) and 3) Regeneration and elongation of guest embryonic neural cells (nested within a container and implanted near to the nerve lesion) through sieve electrode to penetrate to the distal part of the nerve [12, 13]. Each of these methods is faced with its special challenges. Extraction of motor and sensory primitive sources of recorded nerve signal in our study, may introduce an advantageous way for neural rehabilitation.

Blind Source Separation (BSS) methods [19-21] seem good solutions for extracting the initial sources contributing in mixed signals. The resolution of such separation improves as the number of recording channels is increased. For neural applications, this may be achieved in recording via MEA. In this paper, Blind Source Separation (BSS) analysis has been applied to the signals recorded from two points over Ulnar nerve in human hand. Two primitive sources of these records were extracted, using both PCA and different ICA methods. Due to the differences in physical parameters and stimulation sources in nerve fascicles, the nerve fascicular signals may be found either uncorrelated or independent (later is stronger condition than former). Here, in order to show the effectiveness of the employed method, similarity between the separated (primitive) sources of the recorded signal (the response of Ulnar nerve), and the Ulnar sensory signal (recorded on pinkie) was evaluated through the correlation analysis [23].

2. Pre processing

2.1.Signal recording and conditioning

Through a clinical trial, surface electrodes of Ag-AgCl were employed to record surface signals over the Ulnar nerve in left hand of a 37 years old man, as depicted in Fig.1. The wrist exciting electrode pair is used to apply 5 V, 1 Hz pulse train on flexor carpi ulnaris. The recording was performed via two pairs of round plate electrodes on top and down Positions on ADM (abductor digiti minimi) muscle.

---
6 - Central Nervous System
7 - Flat Interface Nerve Electrode
8 - Micro Electrode Array
9 - Electromyogram

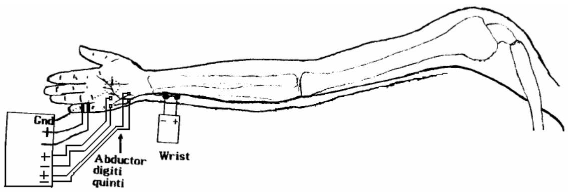

Fig.1: Instrumentation set up used in recording Ulnar nerve

A pair of ring electrodes is used on pinkie to record sensory signal. The electrodes were connected to a high sensitive signal conditioning circuit with voltage gain of 500 (Fig.2) and converted to digital via sound card of the computer.

The recorded ADM signals (which are referred to as mixed sources) and sensory signal (pinkie measurement) are shown in Fig.3. As it is evident, the signals are the responses of the stimulation pulse train.

2.2.Denoising

Although Ag-AgCl electrodes have acceptable measurement noise comparing to the other kinds of electrodes, the recorded signals are seemed noisy. Hence, firstly BSS analysis (here, PCA [22]) was applied to the recorded signals to denoise them.

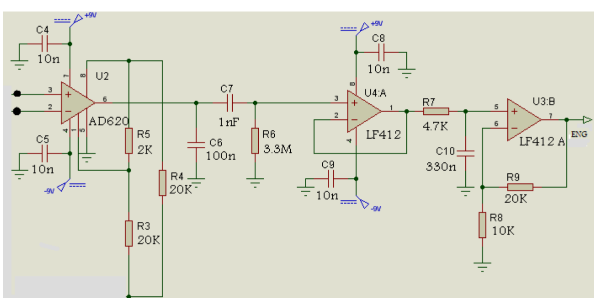

Fig.2. The scheme of read out system

In order to show an example the results of this step, Fig.4 indicates 4 segments of a noisy signal of down point on ADM.

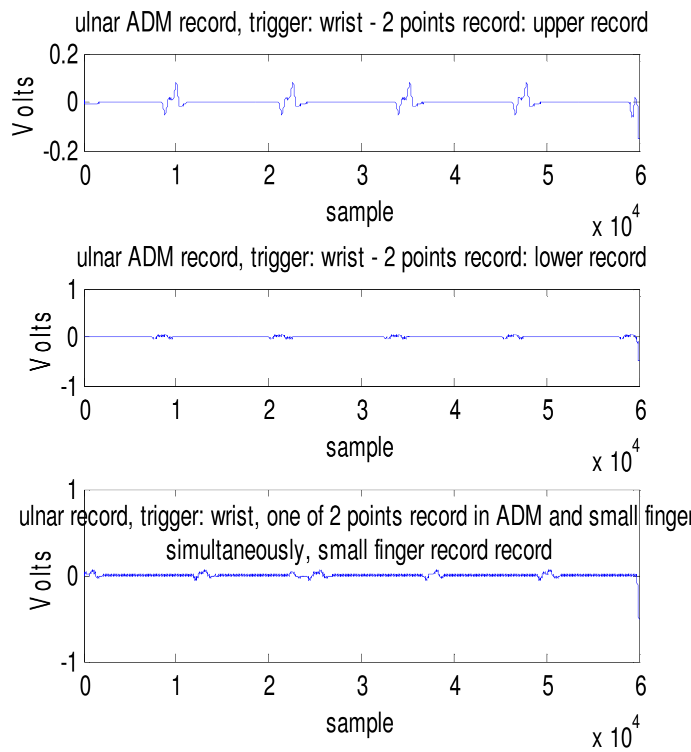

Fig.3. Recorded signals from ADM top point (top), ADM down point (middle) and Pinkie electrodes (bottom) which are in response to 4 stimulation pulses.

Applying the PCA method, removing the smallest eigen value of mixing matrix (which corresponds to the noise) and recombining the rest of the primitive sources in PCA method yields the denoised sources. The results of this step are depicted in Fig.5. The reader can compare ADM down signal in Fig.5 with 4 segments of ADM down noisy signal in Fig.4.

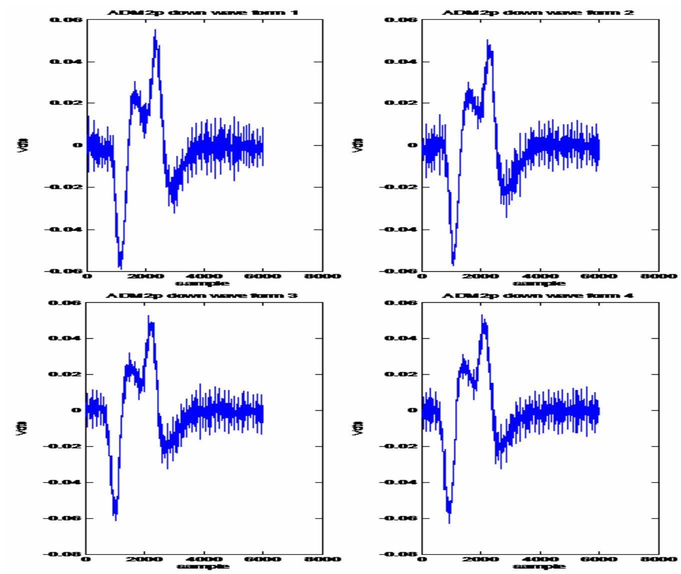

Fig.4. 4 segments of the signal recorded with ADM down sensor, which are seemed noisy

In Fig.5, Three denoised pulses as the representative of ADM up, ADM down and pinkie (sensory) are shown, which are the selected signals for investigating whether BSS methods are applicable in separating mixed ENG signals (ADM up and down signals) into corresponding sensory and motor signals or not.

The method will be discussed in next section.

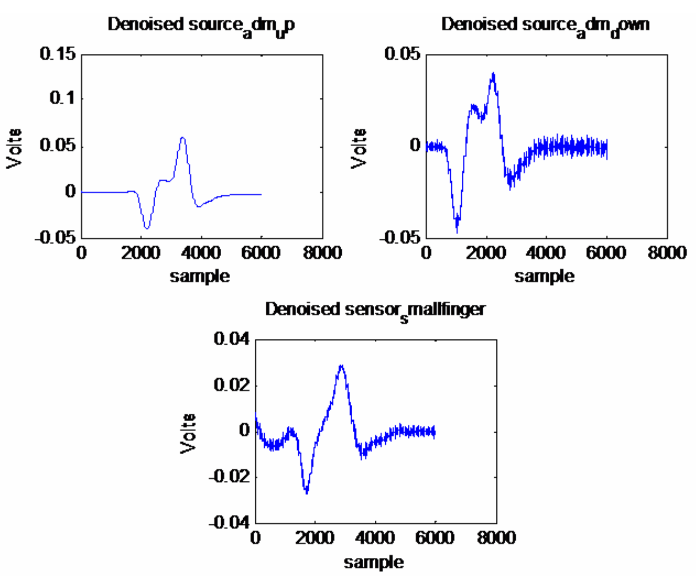

Fig.5. The resulting denoised observations (ADM up, ADM down and Pinkie signals)

3. Methodology

In order to separate the denoised signals of ADM up and ADM down (depicted in Fig.5) into sensory and motor primitive sources, we have employed both PCA and ICA methods. The results and corresponding discussions will be followed bellow:

3.1. Applying PCA to extract uncorrelated resources

PCA method has been applied to two top signals depicted in Fig.5. The achieved eigen spectrums and separated sources are shown in Fig.6 and 7 respectively.

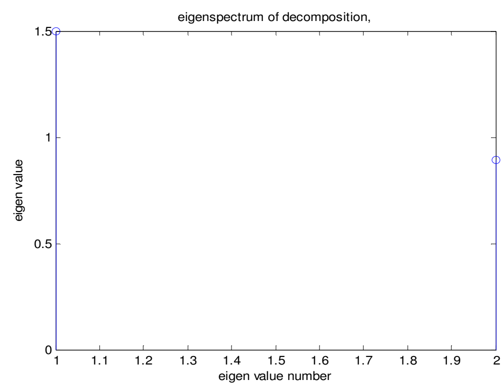

Fig.6. Eigen spectrum corresponding to ADM up and down signals

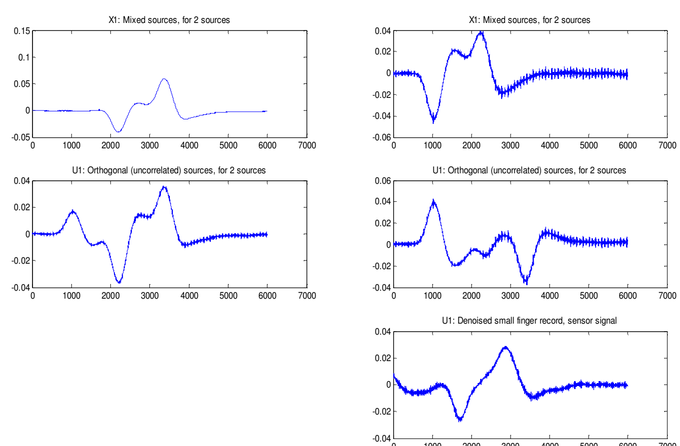

Fig.7. Top row: mixed measured signals, middle row: separated (principal) components, bottom raw: sensory (Pinkie) signal

It is evident from Fig.7 that no significant similarity exists between sensory (Pinkie signal) and each of principal signals. This similarity also can be investigated via correlation functions. Fig.8 shows the Cross correlation function (CCF) between sensory and achieved principal signals.

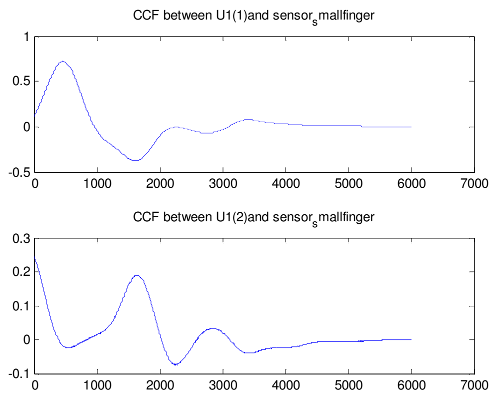

Fig.8. Cross correlation functions between sensory and each of two principal signals

3.2. Applying ICA method to ADM signals

Independent signals are uncorrelated generally. But in contrast, uncorrelated signals are not independent ones in general, except for Gaussian random signals. So, ICA is more powerful method in comparison with PCA. Due to ICA, we will search for signals with distributions as similar to Gaussian distribution as possible. There are some well known cost functions in ICA such as mutual information, entropy or the fourth order moment, kurtosis ($k = v_4 = \frac{E\{(x-\mu_x)^4\}}{\sigma^4}$). Each of these cost functions is a measure of non-Gaussianity to some extent. From the Central Limitary Theorem, we know that the distribution of a sum of independent random variables tends toward a Gaussian distribution. That is, a sum of two independent random variables usually has a distribution which is closer to Gaussian than initial ones. In the other words, independence is non-Gaussianity.

The essential difference between ICA and PCA is that PCA uses variance, a second order moment, rather than higher order statistics (such as the fourth moment, kurtosis) as a metric. The subspace formed with ICA is not necessarily orthogonal (in contrast to PCA). The statistics of neural signals is discussed well in [17, 18].

In ICA literature, the measured sources X can be written as:

$$X = AZ + N \tag{1}$$

where Z is a matrix which contains the independent components, A is mixing matrix and N is measurement noise. During the implementation of ICA, one should try to find a set of components Y with maximum non Gaussianity, which estimates Z (i.e. the primitive independent sources):

$$Y = \widehat{Z} = WX \,, \tag{2}$$

Here, W is called demixing matrix and we have:

$$W = A^{-1} \tag{3}$$

In order to enhance the efficiency of ICA, W is initially extracted via PCA method and the optimization algorithm is started from that point. Some different optimization methods have been tried and Maximum Likelihood method has been selected due to its better results.

3.3. Simplifications on PCA to achieve demixing (W) matrix:

In PCA, mixed sources (X) is related to initial sources (Z) as:

$$X_{m\times n} = A_{m\times m} Z_{m\times n} \tag{4}$$

Using SVD[10] method we have:

$$X_{m\times n} = U_{m\times m} S_{m\times n} V_{n\times n}^{T} \tag{5}$$

We can see that n principal (uncorrelated) sources are located in first n columns of matrix U. Here, comparing two above equations gives us no hint

[10] - Singular value Decomposition

to find matrix A. Instead, one can relate primitive and principal sources as:

$$X_{m\times n} = Z_{m\times n} A_{n\times n} \tag{6}$$

in which $A_{n\times n}$ is a considerably smaller matrix than $A_{m\times m}$ in equation (4). Now, we can compare two equations as bellow:

$$X_{m\times n} = U_{m\times m} \times S_{m\times n} V_{n\times n}{}^{T}$$
$$X_{m\times n} = Z_{m\times n} \times A_{n\times n}$$

In fact, if we consider only n columns of matrix $U_{m\times m}$ (which is identical to $Z_{m\times n}$) and n diagonal element of matrix $S_{m\times n}$ (call it $S'_{n\times n}$), we will have:

$$X_{m\times n} = Z_{m\times n} \times S'_{n\times n} V_{n\times n}{}^{T} \tag{7}$$

$$X_{m\times n} = Z_{m\times n} \times A_{n\times n} \tag{8}$$

Hence, it is concluded that:

$$A_{n\times n} = S'_{n\times n} V_{n\times n}{}^{T} \tag{9}$$

In this way, W is initialized for ICA algorithm as:

$$W_{n\times n} = A_{n\times n}{}^{-1} \tag{10}$$

As it was mentioned before, maximum likelihood method has been employed here to maximizes the distribution's log-likelihood, starting from matrix W above. This maximization leads to the vector (data) with higher Gausianity and more independence with other data vectors. During each iteration of algorithm, the weights are adjusted so that the achieved sources in matrix Y (equation 2) become more independent.

3.4. ICA results:

After applying ICA method to the signals recorded on ADM, the Z sources were achieved as shown in Fig.9. In this Fig., pinkie (sensory) signal is also displayed for comparison.

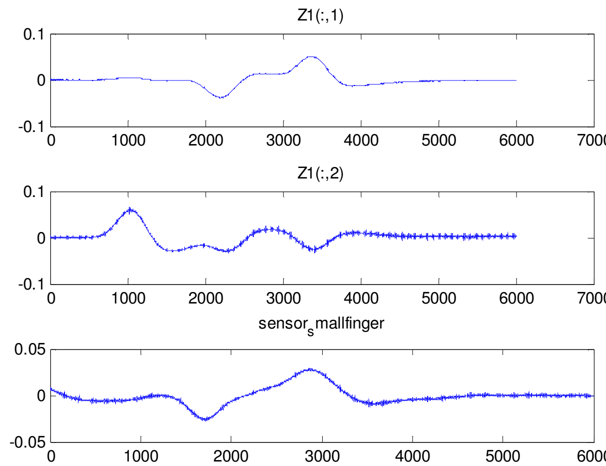

Fig.9. Separated (independent) sources achieved via ICA (two top signals) which are to be compared with pinkie signal (bottom one).

As it is evident from Fig.9, one of the separated sources (top signal) resembles the pinkie signal well. Investigating Cross Correlation Functions (CCF) between ICA primitive sources and the Pinkie signal shows that the CCF between pinkie signal and one of ICA sources depicts high peak near to zero delay (Fig.10).

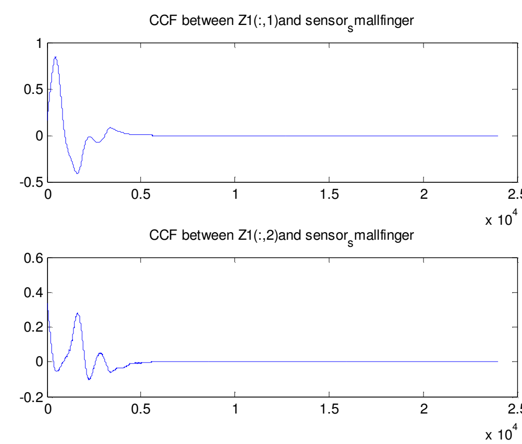

Fig.10: Cross Correlation Functions between ICA primitive sources and pinkie signal. The top CCF shows fairly good degree of similarity rather than the other near to zero delay.

4. Discussion

In this research, BSS analysis has been investigated to see its ability to separate sensory and motor signals contributing in a signal recorded from a nerve. As a trial, the methods have been applied on signals recorded over the ADM muscle in the human hand. ICA method has been tried for this purpose. Fortunately, sensory signal was accessible from pinkie recording. The results of the effectiveness of ICA are shown in Fig.8 and 10 respectively. These two figures show that ICA is capable to detect the primitive signals, as one of its separated sources has good similarity with recorded sensory (Pinkie) signal.

Acknowledgement

This research was fulfilled in Advanced Bionic Systems (ABS) lab in IAUCT. The authors respectfully appreciate Dr. Masoomeh Firoozi and Dr. Pouria Moshayedi from Institute of Biophysics and Biochemistry (IBB), University of Tehran and Dr. Behzad Eftekhar, from Tehran University of Medical Science for their kind motivations and valuable comments; and Dr. Teymuri from Iran University of Medical Science for his kind cooperation in this research.

References

[1] Z. Navarro et al, "A critical review of interfaces with the peripheral nervous system for the control of neuroprostheses and hybrid bionic systems", Journal of the Peripheral Nervous System, Vol.10, pp.229–258, 2005.

[2] Ming-Shaung Ju, Hsin-Chun Chien, Gin-Shin Chen, Chou-Ching K. Lin1, Cheng-Hung Chang, Chi-Wen Chang, "Design and Fabrication of Multi-microelectrode Array for Neural Prosthesis", Journal of Medical and Biological Engineering, Vol.22, No.1, pp.33-40, Accepted 8 April 2002.

[3] A. Harb, Y. HU, M. Sawan, A. Abdelkerim, M.M. elhilali", Low-Power CMOS Interface for Recording and Processing Very Low Amplitude Signals", Analog Integrated Circuits and Signal Processing, Vol.39, pp.39–54, 2004.

[4] Tessler, A., "Intraspinal transplants", Ann. Neurol., Vol.29, pp.115-123, 1991.

[5] Schnell, L., Schwab, M.E., "Sprouting and regeneration of lesioned corticospinal tract fibres in the adult rat spinal cord", Eur. J. Neurosci., Vol.5, pp.1156-1171, 1993.

[6] Schwab, M.E., Kapfhammer, J.P., Bandtlow, C.E., "Inhibitors of neurite growth.", Ann. Rev. Neurosci., Vol.16, pp.565-595, 1993.

[7] Faden, A.I., Salzman, S.K., "The Neurobiology of Central Nervous System Trauma.", Experimental pharmacology. In: Salzman, S.K., Faden, A.I. (Eds.), Oxford University Press, Oxford, pp.227-244, 1994.

[8] Reier, P.J., Anderson, D.K., Schrimsher, G.W., Bao, J., Friedman, R.M., Ritz, L.A., Stokes, B.T., "Neural cell grafting: anatomical and functional repair of the spinal cord", In: Salzman, S.K., Faden, A.L. (Eds.), "The Neurobiology of Central Nervous System Trauma", Oxford University Press, Oxford, pp.288-311, 1994.

[9] Li, Y., Field, P.M., Raisman, G, "Repair of adult rat corticospinal tract by transplants of olfactory ensheathing cells", Science 277, pp.2000-2002, 1997.

[10] P. Decherchia,_P. Gauthierb, "Regeneration of Acutely and Chronically Injured Descending Respiratory Pathways Within Post-Traumatic Nerve Grafts", Neuroscience Vol.112, No.1, pp.141-152, 2002.

[11] M. Firuzi, P. Moshayedi, H. Saberi, H. Mobasheri, F. Abolhassani, MA. Oghabian, "Effects of schwan cell transplantation on recovery of spinal cord injury of rat: A remedy for spinal cord injuries FENS", Federation of European Neurosciences, 4th Forum of European Nerosciences,Hosted by Federation of European Neurosciences Societies (FENS), Lisbon, Portugal, July 10-14, 2004.

[12] Akin T, Najafi K, Smoke RH, Bradley RM, "A micromachined silicon sieve electrode for nerve regeneration applications", IEEE Trans Biomed Eng, Vol.41, pp.305–313, 1994.

[13] Wallman L, Zhang Y, Laurell T, Danielsen N., "The geometric design of micromachined silicon sieve electrodes influences functional nerve regeneration.", Biomaterials, Vol.22, pp.1187–1193, 2001.

[14] Najafi K, Wise KD., "An implantable multielectrode array with on-chip signal processing", IEEE J Solid State Circuits Vol.21, pp.1035–1044, 1986.

[15] Najafi K, Wise KD, Mochizuki T., "A high-yield IC-compatible multichannel recording array", IEEE Trans Electron Devices, Vol.32, pp.1206–1211, 1985.

[16] John W. Clark, Jr., "Medical Instrumentation, Application and Design, chapter 4: The Origin of Biopotentials", Houghton Mifflin Company, 1992.

[17] A.V. Holden, "Lecture notes in biomathematics models of stochastic activity of neurons", Vol. 12, Springer Verlag, 1976.

[18] A. Pappolis, "Probability and stochastic process", Prentice Hall, 1991.

[19] W. Tesfayesus', P. Yoo, D. M. Durand, "Blind Source Separation of Nerve Cuff Recordings" Proceedings of the 25* Annual International Conference of the IEEE EMBS, Cancun, Mexico - September 17-21, 2003.

[20] WTesfayesus and D M Durand, "Blind source separation of peripheral nerve recordings", J. Neural Eng., Vol.4, pp. S157–S167, 2007.

[21] W. Tesfayesus, P. Yoo, M. Moffitt, and D. M. Durand, "Blind Source Separation of Nerve Cuff Recordings", Proceedings of the 26th Annual International Conference of the IEEE EMBS, San Francisco CA, September 1-5, 2004.

[22] Jolliffe IT. "Principal Component Analysis". New York: Springer-Verlag, 1988.

[23] Jezernik S, Grill WM, Sinkjaer T., "Detection and inhibition of hyperreflexia-like bladder contractions in the cat by sacral nerve root recording and electrical stimulation", Neurourol Urodyn., Vol.20, No.2, pp.215-30, 2001.