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EPILEPTIC FOCUS TRACING BASED ON EEG SOURCE LOCALIZATION

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ABSTRACT

Epilepsy is a group of neurological disorders that can have a psychological and emotional impact on people characterized by epileptic seizures. The cause of most cases of epilepsy is unknown. Epilepsy can often be confirmed with an electroencephalogram (EEG). Very fast EEG oscillations having frequencies greater than 70Hz have been observed, immediately before spontaneous seizures. Such oscillations occur in close proximity to the seizure onset sites, and might be a functional indicator of the location of the epileptic focus. Therefore, we could use EEG source localization algorithm to locate the epileptic focus. This paper analysis different source localization algorithm against localization capacity. In addition, looks into a cost efficient multi channel EEG signal acquisition system design.

Keywords: electroencephalography, epilepsy, source localization, inverse problem.

INTRODUCTION

The problem of source localization in EEG has gained significant attention in recent years because of its potential diagnostic value for epilepsy [1], stroke [2, 3], traumatic brain injury [4] and other brain disorders. The human brain interacts by transferring electrical signal through the neurons. These signals provide the directed look into their intricate working. Once the signals were captured, next origin of these signals has to be found, which is called as the inverse problem. As we know, the different part of the brain is responsible for different activity as demonstrated by the Brain Mapping projects. If can pin point their location in space, the complex working of the human brain can be explored. The EEG localization and its application in to a physical brain representation derived by MRI can provide this. However, they suffer a significant lack of spatial resolution. Hence, we rely on functional imaging based on the MRI. This functional imaging is not directly based on the electrical working but the oxygen intake of the parts of the brain. So using the theory that any part of the body that is working will be using oxygen more we show the functionally active portion of the brain. Even though they have been cranked for higher special and spectral resolution they lack the temporal resolution [5]. Electroencephalography source imaging (ESI), which is a technique involving the co registration of EEG and MRI and analysis of the EEG source in three dimensions with the assistance of computer techniques, has been used for the last decade to localize epileptogenic zones noninvasively [6].

Epilepsy is a chronic neurological disorder characterized by occurrence and recurrence of seizures; epilepsy is thus a seizure disorder. A seizure in turn is a “transient of signs and / or symptoms due to abnormal excessive or synchronous neuronal activity in the brain” [7]. About 65 million people worldwide have epilepsy [8] and nearly 80 per cent of the people with epilepsy live in developing countries, where annual new cases occur between 40 to 70 per 100,000 people in the general population. The estimated proportion of the general population with active epilepsy at a given time is between 4 to 10 per 1000 people [9]. A population-based prospective study on epilepsy was conducted over 5 years (2003-8) in Kolkata, India, on randomly selected 100,802 subjects (males 53,209, females 47,593) to assess prevalence as well as to capture incident cases of epilepsy and those incident cases that died. During 2003-2004, a total of 476 subjects with active epilepsy were detected and the age-adjusted prevalence rate was 4.71 per 1000 [10]. Epileptic source localization is a critical diagnostic step for an effective surgical or therapeutically planning. Since anatomical imaging techniques usually do not provide diagnostic information about the location of the epileptic foci, the only way for localization remains to be the EEG and MEG based neuroimaging. Multichannel EEG recorded from the scalp surface provides very valuable but indirect information about the source distribution [11].

SOURCE LOCALIZATION

Source localization is modeling and estimating the spatiotemporal dynamics of neuronal currents throughout the brain that generate the electric potentials and magnetic fields measured with noninvasive or invasive electromagnetic (EM) recording technologies. Unlike the images produced by fMRI, which are only indirectly related to neuroelectrical activity through neurovascular coupling (e.g., the BOLD signal), the current source density or activity images that NSI techniques generate are direct estimates of electrical activity in neuronal populations. In the past few decades, researchers have developed better source localization techniques that are robust to noise and that are well informed by anatomy, neurophysiology, magnetic resonance imaging (MRI), and realistic volume conduction physics [12].

For achieving source localization of primary current density one has to model the electrical signals produced by both the primary(i.e., impressed) and the secondary (i.e., volume, return) current density throughout the head volume conductor, which in reality has an inhomogeneous and anisotropic conductivity profile

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Figure-1. The different volume conductor materials (e.g., scalp, skull layers, CSF, gray matter, white matter) have different conductivities and different levels of anisotropy. A realistic head model is derived from T1 weighted MR images of the subject for the solution of the forward problem. The human head is modeled as three homogeneous isotropic conductor layers; the outermost surface being the boundary for the scalp, the intermediate for the skull and the innermost being for the brain. After segmentation, the surfaces are triangulated in order to generate the realistic head model or solution to forwarded problem [11].

The goal of inverse modeling, is to estimate the location and strengths of the current sources that generate the measured electrical signal data Figure-1. This problem of source localization is an ill-posed inverse problem [13]. In the reciprocal situation where there is no value for the system's parameters to account for the observations, the data are said to be inconsistent (with the model). Another critical situation of ill-posedness is when the model parameters do not depend continuously on the data. This means that even tiny changes on the observations (e.g., by adding a small amount of noise) trigger major variations in the estimated values of the model parameters. This is critical to any experimental situations, and in MEG/EEG in particular, where estimated brain source amplitudes are sought not to 'jump' dramatically from millisecond to millisecond [14].

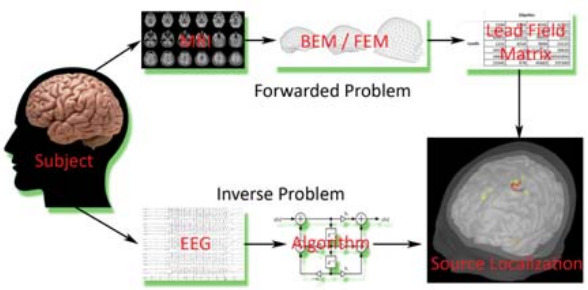

Figure-1. Source localization diagram.

DIFFERENT LOCALIZATION ALGORITHM

Equivalent dipole or Equivalent current dipole source localization models it sources as electromagnetic dipoles located some wherein the brain and uses a fixed number of sources. Scanning method is to overcome the problem of local minima, is the use of a scanning method. These methods use a discrete grid to search for optimal dipole positions throughout the source volume. Source locations are then determined as those for which a metric computed at that location exceeds a given threshold. While these approaches do not lead to a true least squares solution, they can be used to initialize a local least squares search [15]. The Bayesian approach is a statistical method to incorporate a priori information into the estimation of the sources. The types of a priori information that have been incorporated in this approach include information on the neural current [16], the focal nature of the sources, combined spatial and temporal constraints [17], as well as strategies to penalize ghost sources. Distributed source localization estimates the amplitudes of a dense set of dipoles distributed at fixed locations within the head volume. These methods are based on reconstruction of the brain electric activity in each point of a 3D grid of solution points, the number of points being much larger than the number of electrodes on the scalp. Each solution point is considered as a possible location of a current source thus, there is no a priori assumption on the number of dipoles in the brain. This leads to the application of different assumptions in order to identify the "optimal" or "most likely" solution. The methods described in literature differ in their choice and implementation of these assumptions. The constraints can be based on mathematics, on biophysical or physiological knowledge or on findings using other imaging modalities. The validity of these methods is defined by the validity of the assumptions. In the next sections, methods most often described in literature are explained in more detail Figure-2.

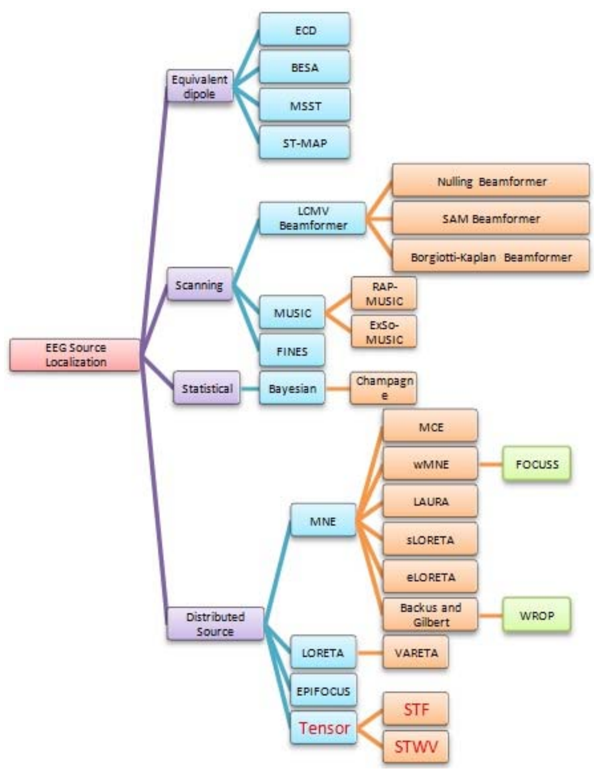

Figure-2. Different source localization algorithm.

TENSOR

To separate several simultaneously active patches and to reduce the background activity, tensor-based preprocessing can be applied. The idea of this method consists in exploiting the structure of three way data which is obtained by applying a transform to the two dimensional measurements. Under the hypothesis that the resulting data, which depends on three variables, is tri linear, the tensor can be decomposed in a unique way (under mild

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conditions) up to scale and permutation ambiguities into separate characteristics for each variable with the help of the CP decomposition. It is thus possible to get an accurate estimate of the spatial mixing matrix or the signal matrix without imposing statistical constraints on sources (unlike Independent Component Analysis (ICA)), which may be physiologically difficult to justify.

Space time frequency (STF) is often used technique for the time frequency analysis of EEG data consists in applying a wavelet transform to the time signals of the different channels. In order to decompose the tensor W using the CP decomposition, we assume that for each extended source, the time and frequency variables separate, leading to a trilinear tensor. This is approximately the case under the hypothesis of oscillatory signals [18].

Space time wave vector (STWV) tensor If a local spatial Fourier transform is calculated within a certain region on the scalp, selected by the spherical window function W(r′–r) centered at sensor position r. Under the assumption that the space and wave vector variables separate for each extended source, which is approximately the case for superficial sources, the tensor F can be approximated by the CP model and be decomposed into space, time, and wave vector characteristics. In the case of the STWV analysis, the temporal characteristics constitute a good approximation of the signal matrix S. An estimate $\hat{H}$ for the lead field matrix H can thus be obtained from the pseudo inverse of the estimated signal matrix $\hat{S}$ and the data matrix X [19].

Whereas previous references on STF and STWV analyses have provided only intuitive conditions concerning their applicability in practical situations, in the Analysis of the trilinear approximation section of the Supplementary material of this paper, we have derived sufficient conditions under which the application of the STF and STWV techniques is justified. Although these mathematical conditions are very restrictive and it is difficult to translate them in to physiological conditions, which can be verified in practice, we will subsequently discuss several points which can be deduced from the identified conditions and which influence the functioning of the STF and STWV analyses.

- Source strengths: For a correct separation, the sources should lead to surface measurements of comparable strengths. Sources with significant differences in amplitude or combinations of deep and superficial sources often lead to the identification of the source with the highest surface amplitude only
- Correlation of the source time signals: The time signals of the different sources should not be too correlated. Low correlations facilitate the source separation
- Correlation of the spatial mixing vectors: For close sources, the spatial mixing vectors are highly correlated, making the source separation difficult. Distant sources, on the other hand, lead to a limited spatial correlation and favor the source separation
- Time frequency or space wave vector characteristics: The STF analysis assumes the time–frequency content of each source to be of rank 1and the STWV analysis is based on the hypothesis of a rank-1 space–wave vector content of each source. In practice, it is generally sufficient if the singular values of the time frequency or space wave vector matrix of each source decrease quickly

ELECTRODE AND MONTAGE

Electrode

Biologic systems frequently have electric activity associated with them. This activity can be a constant dc electric field, a constant flux of charge-carrying particles or current, or a time-varying electric field or current associated with some time-dependent biologic or biochemical phenomenon. Bioelectric phenomena are associated with the distribution of ions or charged molecules in a biologic structure and the changes in this distribution resulting from specific processes. These changes can occur because of biochemical reactions, or they can emanate from phenomena that alter local anatomy.

The silver–silver chloride electrode is one that has characteristics similar to a perfectly nonpolarizable electrode and is practical for use in many biomedical applications. The electrode consists of a silver base structure that is coated with a layer of the ionic compound silver chloride. Some of the silver chloride when exposed to light is reduced to metallic silver, so a typical silver–silver chloride electrode has finely divided metallic silver within a matrix of silver chloride on its surface. Since the silver chloride is relatively insoluble in aqueous solutions, this surface remains stable. Because there is minimal polarization associated with this electrode, motion artifact is reduced compared to polarizable electrodes such as the platinum electrode. Furthermore, due to the reduction in polarization, there is also a smaller effect of frequency on electrode impedance, especially at low frequencies [20].

Montage

The EEG Montage refers to the way the electrodes are placed and how the signal is acquired from the scalp. Montage not only say about the placement of the electrode but also tell the way the electrode are connected to the amplifier.

Bipolar: In bipolar montage, the differential amplifier is connected to two adjacent electrode Figure-3. Referential: In referential system, an electrode is paired with a reference the different method use different reference selection Figure-3.

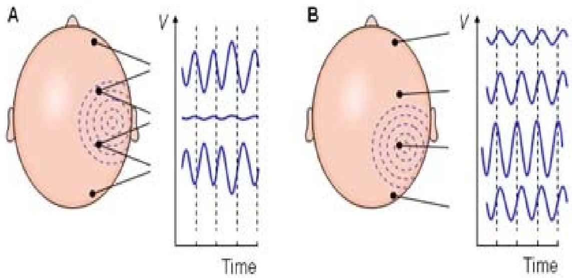

Figure-3. Bipolar is shown in left and referential is shown in right.

EEG ACQUISITION SYSTEM

The human medical data acquisition system, in particular the patient monitoring system, presents the challenge to designers of measuring very small electrical signals in the presence of much larger common-mode voltages and noise. Front-end amplifiers perform the essential conditioning that complements downstream digital processing, which in turn refines the measurement and communicates with other systems. Biophysical measurements include electrical and mechanical signals for general monitoring, diagnostic and scientific purposes both in clinic and non-clinic environments. Successfully meeting the signal acquisition challenge requires system designers to have knowledge of the signal source, good design practice and ICs with appropriate characteristics, features and performance [21].

ADC (Analog to Digital Converter) is the heart of the data acquisition system. The capability of the system to acquire data is directly related to the ADC configuration. Selecting the proper ADC for a particular application appears to be a formidable task, considering the thousands of converters currently on the market. A direct approach is to go right to the selection guides and parametric search engines, such as those available on the manufacturer website. Enter the sampling rate, resolution, power supply voltage, and other important properties and hope for the best. High-performance data acquisition signal chains used in industrial, instrumentation, and medical equipment require high dynamic range and accurate signal measurements while simultaneously addressing tough space constraints, thermal, and power design challenges. One of the ways to achieve a higher dynamic range is to oversample the converter to accurately monitor and measure both small and large input signals from the sensors. Oversampling is a cost-effective process of sampling the input signal at a much higher rate than the Nyquist frequency to increase the signal-to-noise ratio (SNR) and resolution or effective number of bits (ENOB).
As EEG signals are low frequency signals that are of the range of 0.5 Hz to 150 Hz and low amplitude of the rage of few micro volt. What we require is a ADC comfortable in low frequency operation with high resolution and low noise values. Hence Sigma Delta ADC where chosen instead of Successive Approximation ADC. Noise reducing by noise envelope shaping, dynamic range increased by oversampling is decisive factor. The deal was sealed by the fact of power line artifact rejection and anti-aliasing property. As the number of channel required for processing the EEG signal is great the selection of the individual IC will determined by the following parameters. This parameters are cost of unit, cost per channel, offset error, offset error drift.

After analyzing different IC manufactures product list three IC from three different manufactures where finalized. The finalizing is based on the conditions given in the above subsection. There properties are compiled in the above Table-1 for proceeding with the final selection of a single IC.

The ADC AD7718 was chosen as the ADC for the system based on its lowest Min flicker free measured voltage 37.09µV, its cost effectiveness and other properties which are comparable Table-2. ADS1299 has superior capability in terms of date transfer speed. Which will be decisive factor when multiple parallel ADC are employed in the conversion of multi channel data such as EEG. For demonstrating the capability of my current system such a ADC is not required.

Table-1. ADC IC selection data.

	ADS1299	AD7718	MCP3903
Manufacturer	Texas Instruments	Analog Devices	Microchip
Price	Rs 3500	Rs 750	Rs 318
No of Channel	8	10	6
Cost per Channel	Rs 437.50	Rs 75	Rs 53
Offset Error	60 µV	29 - 31 µV	3 mV
Offset Error Drift	80 nV/^{0}C	200 nV/^{0}C	1 µV/^{0}C
Resolution	24	24	24
Effective Resolution	Ref Table 2	10	Ref Table 2
Data Rate	16 Ksps	1.365 Ksps	31.25 Ksps
Package & Pin No	TQFP 64	TSSOP 28	SSOP 28
Analog Voltage	5V	3.3V or 5V	5V
Digital Voltage	3.3V	3.3V or 5V	3.3V
Interface	SPI	SPI	SPI
Interface Speed	14 MHz	4 MHz	10 MHz
Power	40 mW	3.84 mW	84 mW

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Table-2. Effective resolution calculation.

IC	Offset Noise (V)	PGA Gain	Noise / Range	SNR	ENOB
ADS1299	6E-05	1	6.67E-06	103.522	17
		2	1.33E-05	97.501	16
		4	2.67E-05	91.481	15
		6	4.00E-05	87.959	14
		8	5.33E-05	85.460	14
		12	8.00E-05	81.938	13
		24	1.60E-04	75.918	12
AD7718	3E-05	-	7.58E-04	62.409	10
MCP3903	0.003	1	3.00E-03	50.458	8
		2	6.00E-03	44.437	7
		4	1.20E-02	38.416	6
		8	2.40E-02	32.396	5
		16	4.80E-02	26.375	4
		32	9.60E-02	20.355	3

The low bandwidth, high resolution ADCs has a resolution of 16 bits or 24 bits. However, the effective number of bits of a device is limited by noise. This varies depending on the output word rate and the gain setting used. Some companies specify this parameter as effective resolution. Analog Devices specifies peak-to-peak resolution, which is the number of flicker-free bits and is calculated differently from effective resolution. This application note distinguishes between peak-to-peak resolution and effective resolution [22, 23].

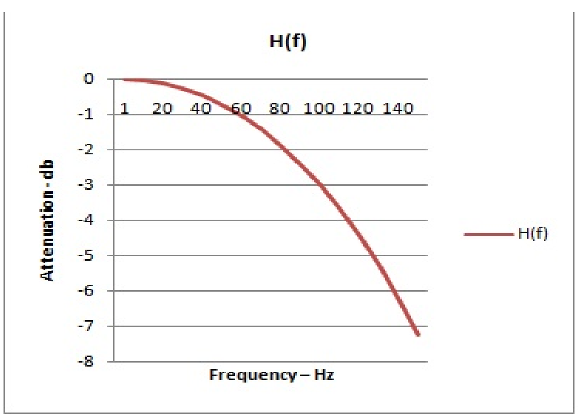

Figure-4. ADC filter response.

RESULT

The data was acquired using the 44 channel EEG system 40 channel data and 4 reference. Then the data is passed on to arduino board using SPI interface. The board based on Arduino UNO architecture act as a buffer and send the data to PC using its onboard UART to USB converter circuit. The PC collects the data and compiles into a mat file, which can be imported into the Brainstorm [24] toolbox for source localization and visualization Figure-5, 6.

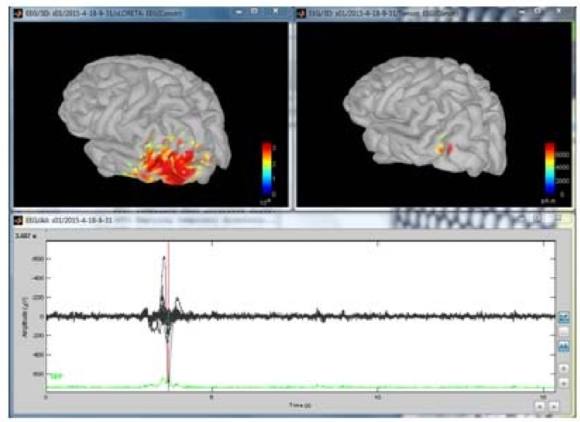

Figure-5. EEG source localization of a spike using sLORETA and tensor using recoded data.

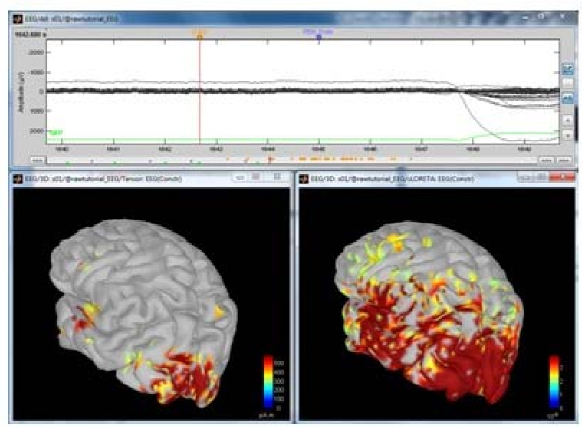

Figure-6. Standard data from an epileptic patient data.

The information show great deal of source localization in case of standard test data as well recoded data. This is great in case of source localization algorithm applied of data, which are based on more than active spot. The algorithm needs to study further with more data see if the localization is not local minimum due to inefficiency of algorithm. This can only be understood by studding the algorithm using lot of data. In addition, study comparison of the data with other source localization algorithm could revile much more to the behavior of the algorithm. AS the source localizations ill-posed problem with result approximated an exact prediction will be difficult.

The data acquisition system show less error when the noise matrix is analyzed. The noise could of course be distributed with over all channels, in which case the noise could be missed. Theoretical calculation puts the noise in between 30 μV - 60 μV. First look on the acquired data show this has been reached. True contribution will be reviled once lone term measurements are done. This will add more time variant factor such as temperature coefficient; offset drift etc in to the mix. This with non-time bound factors such as circuit parasitic components; signal interference etc could surpass the expected noise level.

CONCLUSIONS

The literature review concludes that the tensor based source localization algorithm has better chance of achieving a realistic solution for inverse problem. The tensor approach can solve the inverse problem; the solutions can be made unique with the comparison to the psycho physiological state of the patient at time of recording. Another great advantage is sparse reduction. Almost all algorithms in one point or the other use sparse to enhance the output. However, the sparse inherently is an imaginary quantity and hence will degrade diagnostic vale of the result. Source localization based on solving the inverse problem as explained at start has infinite solution hence any solution will not work as a magic bullet to solve it. Researches are required to incorporate newer and upcoming mathematical and processing technology in to the field of neuro source imaging. The hardware demonstrated its capability of acquiring data for successful source localization. The noise levels were acceptable so was the response time of the system. The system was to acquire data without missing samples. Tensor based source localization show much better source localization than the sLORETA. The computation requirement was management by acquiring and processing small amount of data at a time. As the tensor based algorithm less relies on sparse. The amount of source localization relevance could be better. Further studies are required to confirm this fact.

The possible future work could concentrate in different areas, which can be broadly classified in to hardware and algorithm based. The hardware based could concentrate on achieving better special resolution, noise immunity, real-time processing, portability etc. Spatial resolution is the major concern in development of EEG based source localization into a clinical functional imaging system. The resolution is no way comparable to the fMRI based function imaging. In addition, it has little prediction capability in case of deeper tissue structures. In other hand, MEG has better deep tissue analyzing capability. Noise immunity can further make the source localization precise to the current system. The noise is not just the instrumentation noise or signal interference but biological signal influence such as ECG, EMG, EOG, ERG etc. Immunity to this could further validate the fictional information predication. Algorithm improvement could focus on areas such as faster algorithm with better localization and unique solution closer to the actual biological event. The solution of ill-posed problem can open door for possibility of function database investigation during physically intensive state of body. This could help further study the brain and understand what make the uniqueness that lead to the long achievement of humanity.

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