A NEURAL NETWORK BASED IMAGING SYSTEM FOR fMRI ANALYSIS IMPLEMENTING WAVELET METHOD

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ABSTRACT:- fMRI is a diagnostic imaging method, which is based on the magnetic resonance phenomena. The BOLD technique (Blood Oxygen Level Dependent) is a common technique, which is used for fMRI as it identifies areas in the brain with a high level of oxygen in the blood. The high oxygen level indicates of increasing activity level of the same area in the brain, thus the fMRI experiment aim is to find the active sources in the brain during a specific activity. The problem of separating the sources from the fMRI data sequence can be treated as a Blind Source Separation problem (BSS). This paper deals with different methods of achieving a solution for the Blind Source Separation problem using sparse representations and implementing them for genuine fMRI data sequences by using wavelets.

KEYWORDS: - BOLD, BSS, Wavelet Packet, PET, ICA_NEWTON, PCA.

1.INTRODUCTION OF fMRI:

Functional MRI is used to observe both the structures and also which structures participate in specific functions fMRI, provides high resolution, noninvasive reports of neural activity detected by a blood oxygen level dependent (BOLD) signal. fMRI is based on the increase in blood flow to the local vasculature that accompanies neural activity in the brain. This result in a corresponding local reduction in deoxyhemoglobin because the increase in blood flow occurs without an increase of similar magnitude in oxygen extraction. Since deoxyhemoglobin is paramagnetic, it alters the T2* weighted magnetic resonance image signal. The main advantages to fMRI to image brain activity related to a specific task or sensory process include: 1) The signal does not require injections of radioactive isotopes. 2) The total scan time required can be very short, i.e., on the order of 1.5 to 2.0 min per run (depending on the paradigm). 3) The in-plane resolution of the functional image is generally about 1.5 x 1.5 mm although resolutions less than 1 mm are possible. To put these advantages in perspective, functional images obtained by the earlier method of positron emission tomography, PET, require injections of radioactive isotopes, multiple acquisitions, and, therefore, extended imaging times. Further, the expected resolution of PET images is much larger than the usual fMRI pixel size.

1.1 FUTURE ROLE IN UNDERSTANDING THE PHYSIOLOGICAL BASIS FOR COGNITIVE AND PERCEPTUAL EVENTS

Due to the ability to image the entire 3-dimensional volume of brain, fMRI is capable of isolating many simultaneous and coordinated brain events. This "multi-level" view of brain activity can include "executive" functions and high-level cognitive tasks simultaneously with the primary and secondary input such as vision and audition as well as cerebella contributions. We are currently applying fMRI methods to identify brain structures uniquely the execution of visually guided responses, and complex problem solving. These aspects of brain function have not previously been scrutinized with such precision, and represent some of the remaining frontiers in Neuroscience.

Based on our initial investigations, these future directions include neurosurgical planning and improved assessment of risk for individual patients, improved assessment and strategies for the treatment of chronic pain, improved seizure localization, and improved understanding of the physiology of neurological disorders.

2. BLIND SOURCE SEPARATION PROBLEM

The active structure of the brain consists several independent sources, which are responsible for different kinds of activities. The sources shape is space invariant while their intensity is not. The problem of separating sources from fMRI data sequences may be treated as "Blind Source Separation" (BSS).

Overlooking noise, the problem can be presented in the following matrix form:

$$\begin{pmatrix} M_1 \\ M_2 \\ \vdots \\ M_i \end{pmatrix} = \begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1j} \\ a_{21} & a_{22} & \cdots & a_{2j} \\ \vdots & \vdots & \ddots & \vdots \\ a_{i1} & a_{i2} & \cdots & a_{ij} \end{pmatrix} \cdot \begin{pmatrix} S_1 \\ S_2 \\ \vdots \\ S_j \end{pmatrix} \Leftrightarrow \boxed{\underline{M} = \underline{\underline{A}}\,\underline{S}}$$

When $\underline{S}$ presents a vector of sources, $\underline{\underline{A}}$ presents a matrix of combination's coefficients and $\underline{M}$ presents a vector of mixtures. In order to separate the sources vector $\underline{S}$ from the given mixtures vector $\underline{M}$, to find the inverted matrix of $\underline{\underline{A}}$:

$$\boxed{\underline{S} = \underline{\underline{A}}^{-1} \cdot \underline{M}}$$

2.1 BLIND SOURCE SEPARATION SOLUTION

To solve BBS problem, we have used two methods:

- Geometric separation method (effective with two sources).
- ICA algorithm using Newton optimization Method.

As for the first method, carry out two stages: **First**, we have checked the separation of one-dimensional signals by creating two Gaussian signals and making a linear combination to receive two mixtures. Then, show the mixtures graphically to two crossing lines, which meet, at the zero point. Afterwards, create a kind of a filter of removing the disturbing points near the zero in order to achieve a better separation. Then use the statistical method which is known as histogram in order to calculate the mixture matrix by the lines slopes and then, separating the sources. **Secondly**, receive two images and shape from its values to two-dimensional matrices. To simplify the separation process, from the two original images, create a linear combination and get the mixtures. Then slice the two mixtures to vectors and separate the sources. For comparison, in case of using two sources only, find with the help of the error criteria (MSE) that by using the fast ICA_Newton method to get better results for separating rather than using the geometrical method.

2.2 THE GEOMETRICAL SEPARATION METHOD

2.2.1 SEPARATION PROCESS:

Presenting the signals mixture in matrix form, as follows:

$$\begin{pmatrix} M_1 \\ M_2 \end{pmatrix} = \begin{pmatrix} a & b \\ c & d \end{pmatrix} \cdot \begin{pmatrix} S_1 \\ S_2 \end{pmatrix} \qquad A \equiv \begin{pmatrix} a & b \\ c & d \end{pmatrix}$$

Assuming, that matrix A which presents the mixture matrix isn't singular (reversible):

$$\begin{pmatrix} S_1 \\ S_2 \end{pmatrix} = \underline{\underline{A}}^{-1} \cdot \begin{pmatrix} M_1 \\ M_2 \end{pmatrix} \quad \Rightarrow \quad \begin{pmatrix} \tilde{S}_1 \\ \tilde{S}_2 \end{pmatrix} = \frac{1}{ad-bc} \cdot \begin{pmatrix} d & -b \\ -c & a \end{pmatrix} \cdot \begin{pmatrix} M_1 \\ M_2 \end{pmatrix}$$

Definition:

$$\tilde{A} = A^{-1} = \begin{pmatrix} \tilde{a} & \tilde{b} \\ \tilde{c} & \tilde{d} \end{pmatrix} \quad when \quad \frac{\tilde{c}}{\tilde{a}} = \frac{c}{a} \quad \frac{\tilde{d}}{\tilde{b}} = \frac{d}{b}$$

When $\frac{c}{a}$ and $\frac{d}{b}$ values are known from the slopes of the two crossing linear lines.

For convenience, normalize the coefficients, as follows:

$$\begin{cases} \tilde{a} + \tilde{c} = 1 \\ \tilde{b} + \tilde{d} = 1 \end{cases}$$

Therefore,

$$\boxed{\begin{pmatrix} \tilde{S}_1 \\ \tilde{S}_2 \end{pmatrix} = \underline{\underline{\tilde{A}}} \cdot \begin{pmatrix} M_1 \\ M_2 \end{pmatrix}}$$

When $\underline{\underline{\tilde{A}}}$ presents the reverse mixture matrix and vector $\underline{\tilde{S}}$ presents the vector of the separated sources. Finally, the separated source:

(For comparison: Right – separated source, Left – original source)

2.2.2 SEPARATION BY USING THE "ICA_NEWTON" ALGORITHM

Independent **C**omponent **A**nalysis algorithm is a method, which attempts to separate the fMRI images, so the separated sources will be statistical independent as much as possible.

This method relies on the following assumptions:

- The distribution of each source is spatial independent: $P(S_i) = \prod_{k=1}^{M} P(S_{ik})$

  When S_{ik} is the k^{th} pixel in the i^{th} source.

- The sources are statistical independent – meaning, the sources common distribution is: $P(S_1, S_2, ..., S_n) = \prod_{i=1}^{n} P(S_i)$
- A linear combination of the sources.
- One source with a gaussian distribution, at the most.

For this method, two stages are carried out:

First, run the fast ICA_Newton algorithm on the mixtures of two images and examined the specific separation.

Secondly, shape more mixtures than sources. For effective separation, use the PCA algorithm for decreasing the mixtures dimension down to sources dimension.

Afterwards, run the fast ICA_Newton algorithm on the mixtures and examine the specific separation.

2.2.3 PCA Algorithm (Principal Component Analysis):

PCA algorithm receives signal of fMRI images and produces orthogonal images with maximum variance of the original signal.

PCA algorithm is used for two main objectives:

- Dimension decrease of the fMRI signal: if m fMRI images are produced from n sources when m>n, we can use the PCA algorithm in order to equal the number of the fMRI images to the number of sources (m=n).
- Orthogonalization of fMRI images which produces better performances of the different separation algorithms.
- After using the PCA algorithm, run the fast ICA_Newton algorithm on the mixtures and examined the separations:

2.2.4 THE ANALYSIS OF THE "ICA_NEWTON" ALGORITHM INPUT PARAMETERS

Shape two mixtures from two images.

<u>1st experiment</u>:

- Display of the error graph pending on the iterations number for the two separated images:

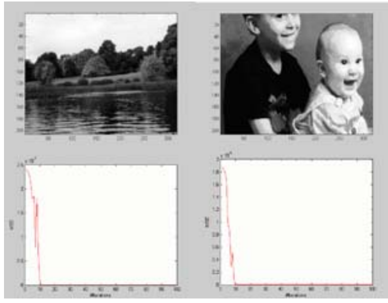

Fig.1

One must point out that from a specific number of iterations, the error comes close to zero and becomes invariant; thus, it's unnecessary to carry out another iterations (such as "saturation")

<u>2nd experiment</u>:

First, examine the smoothing parameter "**lam**" from 0.01 up to 0.1. Then, notice that as long as the parameter is increasing, then the error grows.

But, when the parameter was examined from 0.001 up to 0.01, the outcome was that *the error graph pending on the smoothing parameter "**lam**"* has a minimum point in the test range.

- Display of *the error graph pending on the smoothing parameter "**lam**" for* the two separated images:

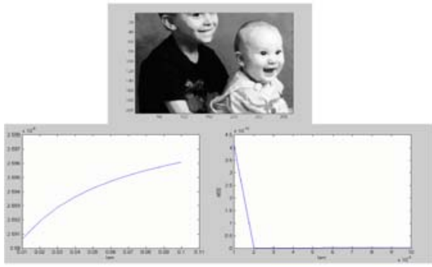

Fig.2

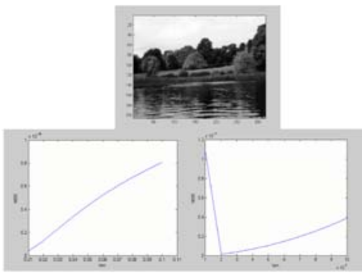

Fig.3

As a summation, in the first experiment (pending on the iterations number), as the increase in the iterations number more than the saturation threshold, the error is invariant. On the other hand, in the second experiment (pending on "**lam**"), one should notice that it is possible to find a minimum point in a specific range, therefore, the parameter can be optimized in order to produce the most from the algorithm. In the genuine fMRI images, it can be noticed that the parameter "**lam**" has a significant effect in order to achieve satisfied results.

3. THE ANALYSIS OF THE fMRI IMAGES

In order to simplify the Blind Source Separation problem, the "Wavelet Packet" method is implemented to find a sparse representation for the images, thus will achieve in satisfied results. This method is significantly preferable than the gradient method using the real data.

3.1 THE SPARSENESS METHOD OF "WAVELET PACKET" (WP)

One dimension "Wavelet Packet" operation:

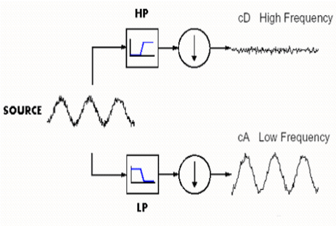

Fig.4

By operating "Wavelet Packet", take a source signal and pass it through a high-pass filter and through a low-pass filter to achieve two signals. In the same way, carry out the same operation on the two output signals and achieve four signals and continue until it is decided to stop at the desirable level. As for the two dimensional case, this operation will be carried out on the columns and rows separately.

As the result of the WP operation, a tree has been shaped with an image in each intersection. Every intersection in a row consists a quarter of the image size from the previous row, as follows: The original image is in the zero level (of the tree). The 4 combinations of filtering the rows and the columns (one time each) are in the first level. The 16 combinations of filtering the rows and the columns (two times each) are in the second level. The 64 combinations are in the third level, etc…

An example of a tree, which consists two levels:

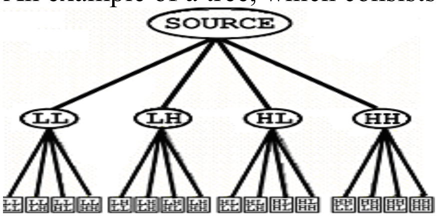

Fig.5

L – Low Pass Filter H – High Pass Filter

High Pass Filter preserves the edges just as they are.

3.2 A COMPARISON BETWEEN THE GRADIENT OPERATION AND THE WP OPERATION IN ORDER TO SPARSE AN IMAGE:

By the gradient operation, shape only one sparse image, as opposed to the WP operation, which have shaped many intersections pending on the tree level. Therefore, one can choose the sparsest intersections from all the possibilities and to produce the sparse mixtures from it. As stated in the WP, pick out the sparsest intersections for each mixture separately and merge it to an image. It's necessary to be consistent and choose the same kind of intersections for the entire mixtures.

3.2.1 SPARSENESS IDENTIFICATION CRITERIA:

Instead of choosing the sparsest intersections by considering the entire intersections' histograms of the whole mixtures, it's preferable to define sparseness criteria, which will be calculated automatically and will classify the intersections for the whole mixtures.

- **'0' norm criteria:**

'0' signal norm is defined as:

$$\|L\|_0 = \sum X_i > Threshold, \quad Threshold > 0$$

In a sparse image, most of its values are close to zero, therefore, as the image become sparser, the image values are being reduced from the threshold so the '0' norm is lower.

- **'1' norm criteria:**

'1' signal norm is defined as: $\|L\|_1 = \sum |X_i|$

As the image become sparser, more of its values are close to zero, thus the '0' norm is lower.

- **Entropy criteria:**

The entropy is a measure of the arrangement in the image. As defines in the following formula:

$$I = -\sum P_i \cdot \log(P_i)$$

In sparse images, most of the pixels are located near the zero point; therefore the entropy is generally lower.

3.3 SIMULATION IMPLEMENTATION ON THE fMRI DATA:

3.3.1 THE ELABORATING PROCESS:

The brain is divided to several segments, so choose a specific segment and run the simulation on it.

3.3.2 BACKGROUND REMOVAL:

The brain background consists most of the image energy. The background isn't an essential data for analysis therefore the separation algorithm can be defected and one should remove it.

The method, which is used to subtract the average of the close images' environment on time plane from the images, is applied. The number of images for averaging is a parameter, which should be optimized, because if chosen overly small environment then the averaging will be too weak. If chosen overly large environment then the required background will be defected, because of the head movements during the medical examination.

3.3.3 DIMENSION REDUCTION BY USING THE PCA ALGORITHM

The number of the required sources is lower than the number of mixtures, thus one should operate the algorithm to reduce the dimension.

3.3.4 SPARSENESS BY USING THE "WAVELET PACKET" METHOD:

The fMRI mixtures don't consist edges, therefore the gradient method doesn't suitable in this case so the WP method is operated (until level 2).

4 THE SIMULATION RESULTS

In the simulated data, there are 16 segments when every segment consists 128 mixtures on time sequence. The 8th segment is picked (the middle) because it's located in the brain center. 8 experiments are carried out in which each have searched for the most powerful and energetic sources.

- In the first experiment, search from the 1st mixture to the 128th.

Afterwards, divide the time to blocks in size of 32 images, and shift 16 images forward in every experiment in order to examine the active sources pending on time and then refer separately to the following time periods:

- In the second experiment, search from the 1st mixture to the 32nd. For third search from the 17th mixture to the 48th. For forth, search from the 33rd mixture to the 64th.For fifth search from the 49th mixture to the 80th.For sixth search from the 65th mixture to the 96th

For seventh search from the 81st mixture to the 112th and finally in the eighth experiment, search from the 97th mixture to the 128th.

Generally, there are 4 to 6 sources in the fMRI data but in the ICA_Newton separation algorithm, the most powerful sources have been chosen.

One should consider the fact that during the medical examination, other sources can be created due to head movements and noise. Occasionally, the additional sources are more energetic than the original sources. Therefore, it is operated on the separation algorithm with much more sources than required.

During the experiments, to search for 16 sources and limited number of the genuine sources are chosen. Finally, examine the required sources.

4.1 THE SEPARATION OUTCOME AND ANALYSIS

- The separation algorithm outcome of the 1st experiment (between the range of 1 to 128 images):

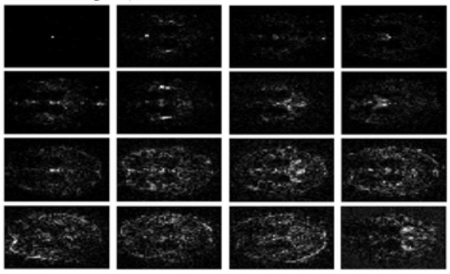

Fig.6

The sources from the 16 separated images:

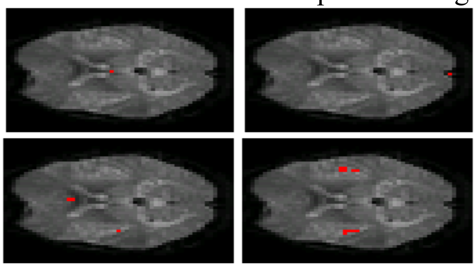

Fig.7

- And the final separation algorithm outcome of the 8th experiment (between the range of 97 to 128 images):

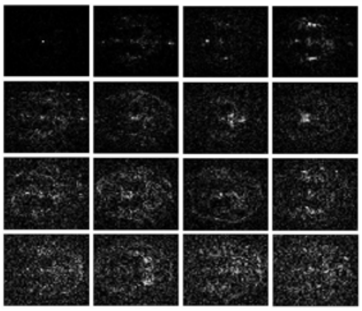

Fig.8

The sources from the 16 separated images:

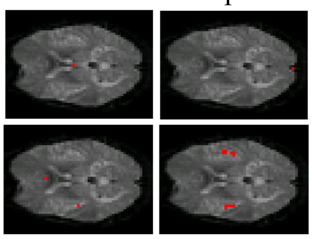

Fig.9

<u>The Active Sources During The Simulation Pending On Time</u>

- In every column, the active sources are located in a range, which is written above.

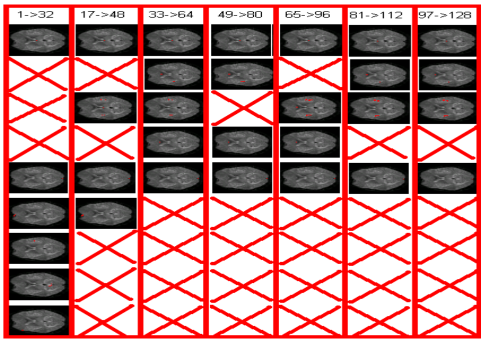

Fig.10

4.2 ARTIFICIAL SOURCE PLANTING:

In order to examine the consistency of the algorithm, an artificial source is planted:

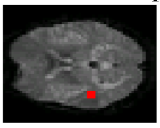

Fig.11

After operating the algorithm between the ranges of 1 to 128, the following results are achieved:

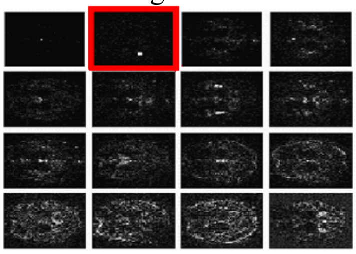

Fig.12

A comparison between the new results and the original results (without the planted artificial source):

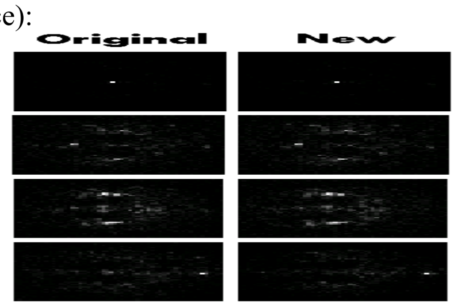

Fig.13

5. CONCLUSIONS

At the first stage, separate one-dimensional sparse signals are done in order to examine the correctness of the algorithm. Afterwards, separation of two dimension images which have been required a preliminary sparseness before running the separation algorithm is achieved. The separation results are satisfying.

The geometric method disadvantage is that it's difficult to suit it for a larger number of mixtures in order to achieve satisfied results, therefore, the ICA_Newton algorithm is used for the second stage, which has separated the images perfectly.

Moreover, the PCA algorithm is implemented which is essential in case that the number of mixtures is bigger than the number of sources. This algorithm reduces the mixture dimension in order to utilize the entire data from the mixtures.

During the fMRI medical examination, head movements and noise appear and despite of the background removal, there are still elements from it, which exist in the mixtures. These factors "break into" the separation algorithm and are interpreted as sources. Thus, although there are nearly 4 to 6 genuine sources, searching is done for 16 images, so that the separation algorithm won't "miss" the genuine sources.

Therefore, the "Wavelet Packet" method is operated while the sparsest intersection is chosen considering the entropy criteria. Several experiments with the fMRI data are carried out first, to examine the active sources for every image range (1 to 128) and afterwards, a range is defined in size of 32 mixtures. Each time, shifting 16 mixtures forward in order to examine the active sources change type pending on time.

Additionally, planting an artificial source in order to examine the consistency of the algorithm and to achieve great and satisfied results carries out another experiment.

REFERENCES:

[1] M. Zibulevsky, P. Kisilev, Y.Y. Zeevi, B.A. Pearlmutter(2000)."Blind source separation via multinode sparse representation", NIPS-2001

[2] Zibulevsky, M. and Pearlmutter, B.A. (1999). "Blind Source Separation by Sparse Decomposition ", Neural Computations 13(4), 2001

[3] M. Zibulevsky, B. A. Pearlmutter, P. Bofill, and P.Kisilev, "Blind Source Separation by Sparse Decomposition", chapter in the book: S. J. Roberts, and R.M. Everson eds., *Independent Component Analysis: Principles and Practice*, Cambridge, 2001

[4] Zibulevsky, M. (2002). "Blind Source Separation with Relative Newton Method"

[5]Bofill P., Zibulevsky, M. (2001). UnderdeterminedBlind Source Separation using Sparse Representations, Signal Processing, Vol.81, No 11, pp.2353-2362

[6] Joseph P. Hornak , Ph.D - The Basic of fMRI – Online version http://www.cis.rit.edu/htbooks/mri/

[7] www.slaney.org (an online book called "Principles of computerized tomography") .