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Localization of Hemorrhage Site in Stroke Patients Using Multichannel Microwave Measurements

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Abstract— **Microwave measurements from an antenna array placed around the head can be used to detect changes in dielectric properties of the brain. In this paper an algorithm is developed to provide localization information of the site of an intra cerebral hemorrhage. The algorithm is based in the hypothesis that scattering parameters for an antenna pair close to the site of the bleeding will undergo larger changes. The change is measured using a feature derived from the scattering measurements using higher order singular value decomposition and is compared with the feature derived from measurements from a control group of healthy subjects. The proposed algorithm is evaluated on clinical data and the result is compared with computed tomography images of the patients.**

***Index Terms*— multichannel microwave measurements, microwave tomography, classification, HOSVD, signal processing, multilinear algebra**

I. INTRODUCTION

Microwave tomography is an emerging affordable diagnostic modality which is based on the changes in the propagation of electromagnetic waves at microwave frequency while passing a medium with varying dielectric property [1]. As blood has a different dielectric constant compared to the brain tissue, a clinically important application of microwave tomography is to localize the site of a hemorrhage in stroke patients. However the image reconstruction in microwave tomography is a nonlinear and ill- posed problem which demands massive calculations and in some cases it is impossible to solve [2]. This paper is devoted to describe a data driven method to provide localization information where measurements from a control group of healthy subjects is utilized.

In the previous paper [3], the main concern was to look at the microwave measurement system as a whole and take all the data as input and detect any changes of the patients data compared to measurements from a controlled group of healthy volunteers. This method was successful and all the patient data could be separated from healthy data. In this paper, the multichannel structure of the system is utilized and channels of patients are compared to their corresponding channels in healthy volunteers. Finding a proper way to measure this change is the core of this paper. These changes are depicted in graphical charts which in turn will reveal the approximate site of hemorrhage inside the head.

In this paper, first the multichannel nature of the measuring device and the obtained measurements are discussed. Then the main idea behind localization of stroke using a multichannel microwave setup is examined. The classification problem and feature extraction process are discussed afterwards. Then a method is suggested which can correlate the extracted features of channels to the site of hemorrhage inside the head. At the end, the actual clinical results are presented.

II. MULTICHANNEL MICROWAVE SETUP

The device which has been used to collect the data consists of an electronic switchbox, a Programmable Network Analyzer (PNA), a computer controlling measurement and an antenna array helmet with 10 triangular micro strip antennas with V-shaped slots and a short circuit wall. Adjustable water containers have been used in between the antennas and the skull for better electromagnetic matching. The antennas have been placed in the helmet in accordance to the international 10-20 system for measurement of EEG signals. The placement of antennas around the skull is shown in Figure 1. A two port PNA is used to perform the measurements of reflection and transmission coefficients. A switch module has been used to control connections and disconnections of the antennas to the PNA.

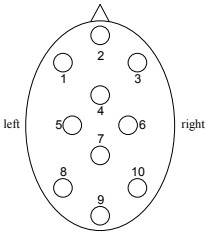

Figure 1: Arrangement of the antennas on the scalp

During a measurement, that takes about 5 minutes, one antenna at a time will send out an electromagnetic signal from 0.1 to 3 GHz where each antenna will act as receiver in sequence. When all antennas received the signal from the first antenna, the second antenna will act as a sender, until

all antennas have both sent and received, resulting in a 10 x 10 pair of measurements.

As it can be observed from Figure 1 the measurement system has a multichannel property which means that in each time slot one particular antennas is sending and one particular antenna is receiving (corresponding to one channel) and in the next time slot this pair (channel) would change. Therefore, each channel will measure the brain in one particular time slot. Since the elapsed time between two consecutive measurements is small, we can claim that different channels are measuring almost the exact same object (brain).

Figure 2 demonstrates how the data in each channel 1 to channel 15 looks like for one particular patient. As it can be seen, data from different channels are totally different and it is hard to find any pattern in data.

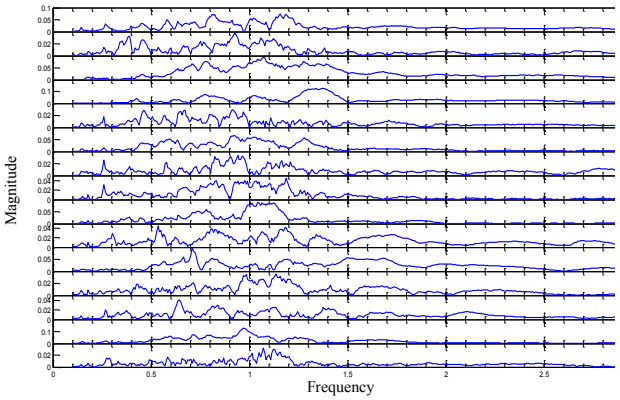

Figure 2: Channels 1 to 15 in multichannel measurement setup for one patient.

III. Localization Idea

In this part we describe the core idea of the localization method which stems from the multichannel property of the measurement system. Consider a case in which for example there is a hemorrhage in central left lobe of the brain as depicted in Figure 3. It is obvious that different antennas have different distances to the hemorrhage site. The main hypothesis which is considered in this case is that the closer the hemorrhage is in the vicinity of the direct pass between two antennas corresponding for one channel, there is a higher probability that the signal will deviate compared with the healthy control group for that channel. It should also be noticed that based on this hypothesis all channels sense the deviation of signals caused by hemorrhage inside the brain with certain probability but this probability is higher for the channels for which the hemorrhage is closer and in between the direct pass between two antennas for that specific channel. For example as depicted in Figure 3, channel (1,4) is more close to the hemorrhage site than channel (9,10).

Therefore we expect the signals for channel (1,4) experience a larger deviation from healthy control group than signals for channel (9,10). On the other hand channel (2,8) are not as close as the channel (1,4) to hemorrhage site but the hemorrhage is close to the direct pass between the transmitting and receiving antennas for this channel. Therefore, we also expect for this channel to experience more deviation from healthy control group than other channels for which the hemorrhage site is not close to direct pass in between the transmitting and receiving antennas for example channel (6,10) and (7,10).

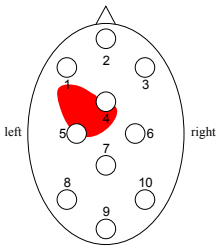

Figure 3: Hemorrhage in central left lobe of the brain

In fact the basis of the localization algorithm is to measure the probability of deviation of the microwave signals due to hemorrhage inside the brain. A smart way would be to consider the different classification probabilities for different channels which depicts the strength of each channel in classifying a patient as patient and is called classification factor for that channel. These classification factors are the basis for the construction of localization charts.

Therefore, in order to calculate the classification factors, we need to use a feature extraction and classification algorithm and implement it to all channels in the system. The classification and feature extraction algorithm is described completely in [3].

A. HOSVD angle

HOSVD angle is the main feature which is used to classify data and the following is the steps to calculate it [3]. First, we stack several training sample matrices together and form a 3D tensor $\mathbf{H}\in\mathbb{C}^{I_1\times I_2\times I_3}$ in which I_1 is different channels, I_2 is frequency range and I_3 is different measurements. In the next step, the mean of all healthy samples should be calculated ($\bar{\boldsymbol{H}}$).

$$\bar{\boldsymbol{H}} = \frac{1}{I_3}\sum_{i=1}^{I_3} \boldsymbol{H}_{::i} \tag{5}$$

Then mean value should be subtracted from each training sample in order to calculate deviations from mean ($\mathbf{H}_{\boldsymbol{d}}$). These data will have the same structure as the original data. Afterwards, for each new measurement ($\boldsymbol{X}$), the deviation from mean will be calculated ($\boldsymbol{X}_{\boldsymbol{d}}$).

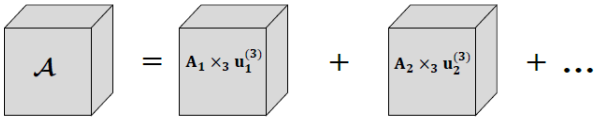

Figure 4: Tensor A as a sum of rank-1 tensors

As discussed in [3], by using HOSVD decomposition it is possible to write each 3rd order tensor $\mathbf{H}_{\boldsymbol{d}} \in \mathbb{C}^{\mathbf{I_1}\times\mathbf{I_2}\times\mathbf{I_3}}$ as the sum of 3rd order rank-1 tensors as showed in Figure 4. The description of a tensor as the sum of rank-1 tensors can be formulated as:

$$\mathbf{H}_{\boldsymbol{d}} = \sum_{\mathrm{i}=1}^{\mathrm{I}_3} \boldsymbol{A}_{\mathrm{i}} \times_3 \boldsymbol{u}_{\mathrm{i}}^{(3)} \tag{6}$$

in which $\boldsymbol{A}_{\mathrm{i}} = (\boldsymbol{\Sigma} \times_1 \mathbf{U}^{(1)} \times_2 \mathbf{U}^{(2)})_{::\mathrm{i}}$ for i =1 to I_3 are

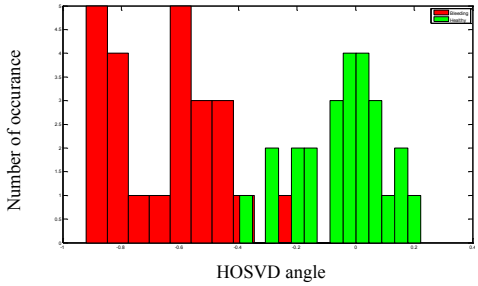

Figure 5: Classification of channel (1,3) for an ICH patient from channel (1,3) for healthy subjects using leave-one-out approach

orthogonal bases with respect to 3rd mode and

$$\mathbf{U}^{(3)} = \left[\mathbf{u}_1^{(3)}\ \mathbf{u}_2^{(3)}\ \dots\ \mathbf{u}_{I_3}^{(3)}\right]$$

In the case of a 3D tensor the bases will be 2D matrices. Using this property of HOSVD, it is possible to construct a subspace based on the training data [3].

Having $\boldsymbol{A_i}$, $\bar{\boldsymbol{H}}$ and $\boldsymbol{X_d}$ we need to calculate the angel between the matrix for new unclassified measurement ($\boldsymbol{X_d}$) and the deviation space constructed on healthy subjects ($\mathbf{H_d}$). The angle $\theta_{\mathbf{X,A}}$ between a matrix $\boldsymbol{X} \in \mathbb{C}^{m\times n}$ and a subspace $\mathbf{A}$ is defined as:

$$\theta_{\mathbf{X,A}} = \cos^{-1}\left(\frac{\langle \boldsymbol{P}_{\mathbf{A}}(\boldsymbol{X}), \boldsymbol{X}\rangle}{\|\boldsymbol{P}_{\mathbf{A}}(\boldsymbol{X})\|.\|\boldsymbol{X}\|}\right) \quad (7)$$

where

$$\boldsymbol{P}_{\mathbf{A}}(\boldsymbol{X}) = \sum_{i=1}^{r} \langle \boldsymbol{A_i}, \boldsymbol{X}\rangle . \boldsymbol{A_i} \quad (8)$$

is the projection of a matrix $\boldsymbol{X} \in \mathbb{C}^{m\times n}$ on a subspace $\mathbf{A}$ presented with orthogonal bases $\boldsymbol{A_i} \in \mathbb{C}^{\boldsymbol{m\times n}}$. $\langle \boldsymbol{X}, \boldsymbol{Y}\rangle$ denotes the scalar product of two matrices $\boldsymbol{X} \in \mathbb{C}^{m\times n}$ and $\boldsymbol{Y} \in \mathbb{C}^{m\times n}$ which is defined as:

$$\langle \boldsymbol{X}, \boldsymbol{Y}\rangle = \sum_{i=1}^{m}\sum_{j=1}^{n} x_{ij} y_{ij}^{*} \quad (9)$$

and

$$\|X\| = \sqrt{\sum_{i=1}^{m}\sum_{j=1}^{n} x_{ij} x_{ij}^{*}} \quad (10)$$

is the Frobenius norm of the matrix $X \in \mathbb{C}^{m\times n}$.

The HOSVD angle ($\theta_{\text{hosvd}}(\mathbf{X,A})$) which is the main feature for classification is defined as:

$$\theta_{\text{HOSVD}}(\mathbf{X,A}) = \theta_{\bar{\boldsymbol{H}},\mathbf{H_d}} - \theta_{\boldsymbol{X_d},\mathbf{H_d}} \quad (11)$$

IV. Localization of Hemorrhage

By having feature values for each channel ready it is possible to test the localization idea discussed in section III in practice.

A. Classification Factor

As it has been discussed in section I the measurement device is consisting of 10 antennas so there is $\binom{10}{2} = \frac{10!}{2!\times 8!} =$ 45 different combinations for two antennas which are called channels and each channel can do the classification to some extent (see Figure 5). The performance of the classifier for each channel can be analyzed using the leave-one-out validation approach. Now if the classification results (using HOSVD angle) for each channel can be assumed to have an almost normal distribution for both healthy subjects and Intracerebral Hemorrhage (ICH) patients, the t-student test can be used to measure the separation between healthy subjects and ICH patients for each channel. The value of this separation is called the Classification Factor (CF) and can be obtained by following formula:

$$CF \triangleq \frac{Mean\ difference\ of\ bleeding\ from\ healthy}{weighted\ average\ of\ bleeding\ and\ healthy\ variances}$$

$$= \frac{(\bar{B} - \bar{H}) - (\mu_B - \mu_H)}{s_p\sqrt{\frac{1}{n_H} + \frac{1}{n_B}}} \quad (12)$$

in which $s_p^2 = \frac{(n_H-1)s_H^2 + (n_B-1)s_B^2}{n_H+n_B-2}$ is the averaged variance, n_H is the number of healthy samples, n_B is the number of ICH samples, $\bar{H}$ is average value of HOSVD angle for healthy samples and $\bar{B}$ is the average value of HOSVD angle for ICH samples. In fact, the null hypothesis is that healthy and ICH samples are the same ($H_0: \mu_B = \mu_H$) and for large value of CF this hypothesis can be rejected [10].

In fact CF measures to what extent one channel has been affected by the hemorrhage and the channels with large value of CF are the most informative. As it can be inferred from the formula there are two parameters that influence the CF for each channel, the difference between mean value of ICH and healthy for one channel and the variance of each channel. As the difference between the mean value of ICH and healthy for one channel is increased the classification factor would increase and as variability of each channel is increased the Classification factor would decrease.

B. Localization Algorithm

The basis for localization algorithm is to find the maximum value for the CFs for each antenna for all possible channels and assign a maximum classification factor to each antenna. It should be noticed that even when the two distributions are not normal, CF can still be a good measure for separation. To sum up, producing the data for localization of the ICH is consisting of 3 steps:

1. Calculating the classification results (using HOSVD angle) for each channel.
2. Computing CF for each channel.
3. Finding the maximum CF for each antenna (CF of each channel is divided between its consisting antennas) and computing **Maximum Classification Factor (MCF)** for each antenna.

By having MCFs ready localization charts can be constructed. In localization charts, antennas which have higher MCFs are shown with brighter red circles and antennas with less MCF with darker circles. For instance if antenna number 2 has the MCF of 80 and antennas number 10 the MCF of 50 and all other antennas have MCF of 10 then the localization chart would look like Figure 6.

It should also be mentioned that, according to the 3D shape of the head, the obtained charts are a simplification of localization of hemorrhage in 2D and are an indication of

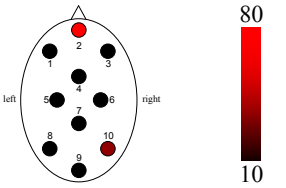

Figure 6: An example of localization chart

the localization of the hemorrhage inside the brain. Having theses charts at hand, the antennas with highest MCF (bright red) construct a simple polygonal shape which shows the area with higher probability of hemorrhage.

V. Experimental Results for Clinical Data

A clinical trial has been performed at Sahlgrenska University Hospital, Gothenburg, Sweden and the data are used to evaluate the developed technique. The described algorithm has been evaluated on the data from ICH patients and some of the results for localization alongside of CT scan images are presented in Figure 7.

As it can be seen in Figure 7, the antennas which construct a direct pass close to the hemorrhage site have larger CF and therefore MCF values and therefore are shown with brighter circles while the antennas for which the constructed pass way is far from the hemorrhage site have smaller CFs and are shown with the darker circles which justify our hypothesis.

VI. Conclusion

In this paper a multichannel structure of the microwave measurement system is utilized to predict the localization of the hemorrhage site in stroke patients. The basic idea of this method is based on the hypothesis that the signals from channels that are close to hemorrhage site experience larger deviation from the signals for the similar channels for control healthy volunteers. The main feature, HOSVD angle, is extracted based on Higher Order Singular Value Decomposition and leave-one-out approach is used for validation of classification for each channel with its similar channels for healthy control group. The performance of the classifier for different channels is evaluated using t-student test to assign a classification factor to each channel. The results are shown alongside with the CT images of the patients for better comparison. The results show that the channels having direct pass way close to the hemorrhage site deviate more and therefore have larger CFs which justifies the main hypothesis.

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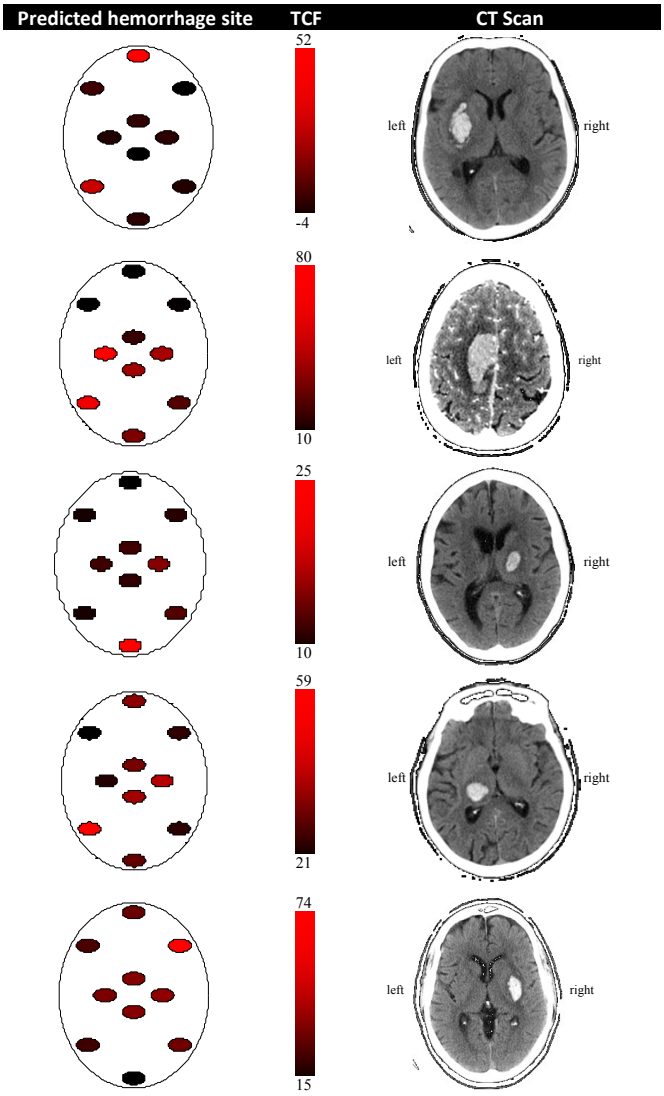

Figure 7: Localization results for clinical data

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