A Novel Machine Learning Approach of Hemorrhage Stroke Detection in Differential Microwave Head Imaging System

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***Abstract*—In this paper, brain hemorrhage stroke detection approach using microwave-imaging system with a novel machine-learning based post-processing method is presented. In order to create a circular array based microwave imaging system sixteen elements of the modified bowtie antennas are simulated in CST medium around the full head phantom. In order to radiate in desired band from 0.5-5 GHz an appropriate matching medium is designed. In addition, a hierarchical preprocessing method is employed to calibrate the reflected signals. In the processing section, a confocal image-reconstructing algorithm based is used. Finally, a new machine learning technique including discrete wavelet transform (DWT) and principle component analysis (PCA) for feature extraction and reduction, respectively. In addition, support vector machine (SVM) is used for segmentation and clustering of hemorrhage stroke detection from reconstructed image is employed. Simulated results are presented to validate the effectiveness of the proposed method for precisely localizing and classifying bleeding targets.**

***Index Terms*—microwave brain imaging system, UWB matched bowtie antenna, confocal image reconctruction algorithm, haemorrhage stroke detection, segmentation and clustering.**

I. INTRODUCTION

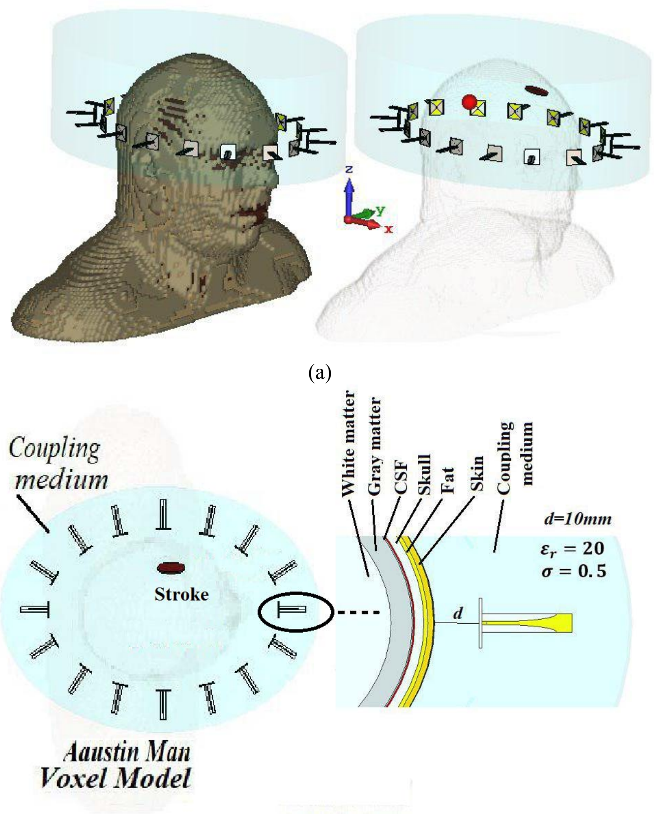
The objective of microwave imaging system for human head imaging applications is detection of cancerous tumor, damaged brain tissue due to ischemic or hemorrhage strokes and brain activities monitoring [1-5]. There are several key factors in the imaging performance such the antenna dimension and its radiation characteristics, image reconstruction methods, post-processing techniques etc. [1-5]. A real time imaging method is needed for the microwave technique to be applicable for pre-hospital use. Several imaging methods have been proposed to utilize in the medical imaging systems. Each of the method has its own compatibility and weak points [6-7].

Machine learning techniques applied to the microwave imaging systems (MIS) have great potential in enabling segmentation, clustering and classification situations. One type of classification is the automatic diagnosis basing on the microwave tomography reconstructed image [8], e.g. to distinguish a malignant and a benign tumor within a breast basing on the dielectric properties reconstructed by microwave imaging system. The other type of classification is directly basing on the feature of signal without the dielectric properties reconstruction. For example, [9-10] differentiate the intra cerebral hemorrhage (ICH) from the ischemic stroke (IS) and the hemorrhagic patients.

In this paper, we explore the advantages of using machine learning technique to localizing and detecting of hemorrhage stroke in the precisely modeled full head phantom in compact multi-static imaging system. In this context, a novel design of compact matched bowtie antenna with a matching balloon in the feed-line is presented. By using these modified structures, the usable upper frequency of the proposed slot antenna is progressed from 0.5 GHz to 5 GHz. By using a hierarchical calibration method and confocal image reconstruction algorithm a brain hemorrhage stroke has been detected and localized inside a full head phantom. The 2D reconstructed image results of this study show that the proposed method has excellent performance for microwave head imaging system applications. In the post-processing section, first the detailed procedures of feature extraction and reduction methods such as discrete wavelet transform (DWT) and principle component analysis (PCA) have been applied. Then, support vector machine (SVM) is used as a classifier and segmentation process. The validity of the presented system and its target detection algorithm has been verified via simulation in examples. Results obtained by the proposed multi-static imaging system prove that this system based on using the proposed machine learning approach has a good ability to finding and segmentation of intracranial hemorrhage strokes.

II. THE PROPOSED MICROWAVE IMAGING SETUP WITH THE ANTENNA CONFIGURATION

The proposed "scenario under test" setup of the head imaging system with sixteen UWB bowtie antennas is shown in Fig. 1. The precisely model of the Austin-Man full human head phantom [11] is inserted in CST microwave studio [12] as presented in Fig. 1. The utilized head phantom contains all anatomical details of the human head including head layers, from skin layer to white matter of the brain for ease of modeling and imaging. All electrical characteristics of the utilized head phantom's materials are given in Table I. In addition, as shown in Fig. 1 (a), sixteen of the proposed antennas encircling the head at equal distances 10 mm from skin layer, and a hemorrhage stroke that located inside the head is shown in Fig.1 (b).



(a)

(b)

Fig. 1. Multi-static UWB microwave imaging system schematic for heamorrahge stroke detection, (a) Simulated head model with a hemorrhage stroke in CST medium, (b) Multi layer structure of the designed head phantom and antenna's positions.

TABLE I. ELECTRICAL CHARACTERITICS OF THE MULTI-LAYER BRAIN PHANTOM

Layer	R(mm)	r(mm)	Depth(mm)
Skin	**120**	**80**	**2**
Fat	**118**	**78**	**1.4**
Skull	**116.6**	**76.6**	**4.1**
CSF	**113.4**	**73.4**	**0.5**
Gray Matter	**112.9**	**72.9**	**7**
White Matter	**105**	**65**	**Inner part**
Blood	**30**	**10**	**-**
Hemorrhage stroke	**14**	**-**	**-**

It is a well-known fact that printed matched bowtie antennas present really appealing physical features, such as simple structure, small size and high gain [13]. The proposed structure is depicted in Fig 2 which is designed based on the antenna presented in Ref. [13] but with a smaller size and higher frequency bandwidth. The square slot antenna fed by a 50 Ω microstrip line, which is printed on an Rogress 5880 substrate with the dimension of 22×22 mm^2, the dielectric constant of 2.2, and the loss tangent of 0.001. The basic antenna structure consists of a radiating patch, a balun type feed line. All dimensions of the antenna are given in Table II.

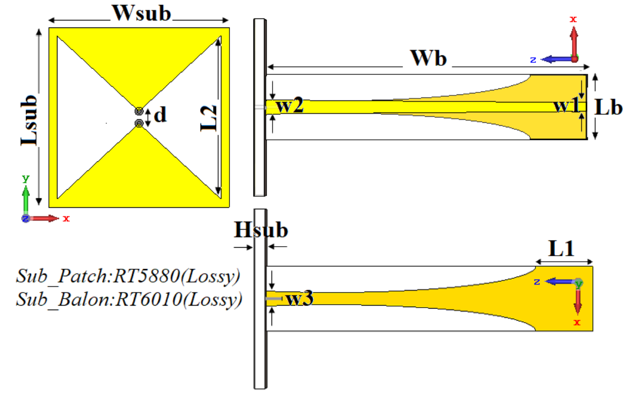


Fig. 2. The proposed matched bowtie antenna with matching balun schematic [13].

TABLE II. THE PROPOSED SLOT ANTENNA DIMENSIONS

Parameter	(mm)	Parameter	(mm)
Wsub	**22**	**Lsub**	**22**
Wb	**40**	**Lb**	**8**
W1	**1.1**	**W2**	**1.75**
W3	**1.84**	**L1**	**7**
L2	**20**	**Hsub**	**1.5**
H_{sub} (Balloon)	**1.27**	**d**	**1.5**

The first step before starting simulation of the microwave imaging setup is designing a matching medium. By shielding antennas in the matching medium, it is possible to decrease the mismatch effects between antenna and head phantom [1]. To ensure electrical matching between antennas and internal of the region under test a coupling medium is designed based on parametric sweep of its electrical characteristics. The calculated electrical characteristics of the coupling medium are $\varepsilon_r = 20$ and $\sigma = 0.5\ S/m$. Fig. 3 shows the simulated return loss characteristics of the proposed antenna in different positions inside the designed matching medium. It can be seen from Fig. 3 that by determining a good choice for permittivity and conductivity of the matching medium all the sixteen antennas are radiated from 0.5 to 5 GHz.

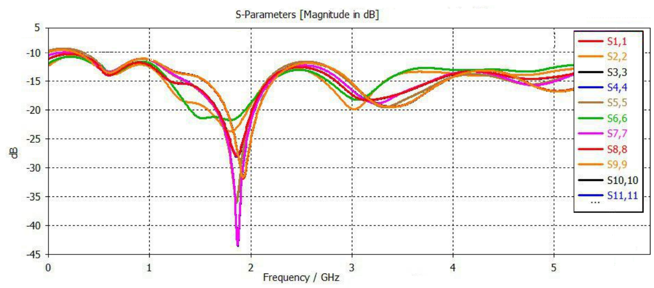


Fig. 3. Siimulated return loss characteristics of the proposed antennas inside the proposed matching medium.

III. THE PROPOSED IMAGE RECONSTRUCTION METHOD BASED ON HIERARCHICAL PRE-PROCESSING

In this section, in order to evaluate the performance of the proposed microwave imaging system, the confocal imaging algorithm is performed and the results are analyzed and discussed. It is obvious detecting hemorrhage stroke from head phantom is a near-filed imaging scenario and it needs to consider as real-time data acquisition. After simulating, the designed imaging setup all of the reflected signals are stored to reconstruct images in MATLAB.

In order to coherent signal integration, we need to compensate effects of delays, which are exist because of the multi-static structure in the reflected signals of different paths. Therefore, at first step of the proposed calibration, it should be considered delay of antennas' positions. For this case, we need to find the phase shifting between each antenna with others. This delay time is equal to direct distance between transmitter and receiver divided by wave velocity in the coupling medium [1]. The next step is extracting hemorrhage stroke location from the reflected signals. After identifying this point, for compensate this delay, we make zero all of the values before their calculated delays. Regarding to multi-static near filed imaging, in in order to reconstruct an image we need to apply a focused beamforming algorithm such as confocal beamforming algorithm. For this, the first step is identifying focal points to calculate energy pattern of the reflected signal at these points, which for multi-static imaging algorithm, it will be done by coherence signal integration. Regarding to pulse-width and region of interest (ROI) dimension we considered 320 focal points inside the ROI.

Before applying confocal algorithm, it is necessary to identify the best choice for effective permittivity of the scattering point. In order to obtain an effective permittivity characteristics of the human head medium, the proposed antenna is placed in front of the point of entry of the human head, which is at the path between antenna and skin layer. The field probes are inserted in different distances into the head model and the antenna, which is excited with the frequency band of interest and run in CST. The best choice for effective permittivity from the point of entry is calculated 38.9 in the proposed study case.

The confocal beamforming algorithm for brain hemorrhage stroke detection is an easy and robust technique for hemorrhage stroke detection, which is used dealy-and sum (DAS) for coherenet signal integration to approximate the precise location of the hemorrhage stroke [4]. By assuming that the wave inside the biological tissue phantom has a spherical wave front and $X_i(n)$ be the complex received signal from antenna, the output $F_i(n)$ represents the intensity (brightness) of the picture pixel at the n^{th} range cell and direction θ and is given by the following relation

$$F_i(n) = \sum_{n=1}^{N} f_i . X_i(n) . e^{j\varphi_i} \qquad (1)$$

Where N is the total number of receiving antennas, f_i is the correction for phantom medium attenuations and propagation loss and was assumed constant because of the same signal incidence angle. The phase component φ_i is applied to compensate for the phase difference due to distinct traveling paths [1].

Through processing raw data, the 2D reconstructed image using the differential imaging scenario by subtracting a healthy brain image from the brain with stroke is shown in Fig. 4. As mentioned before in conventional confocal, dealy and sum beamforming is used. As illustrated in Fig. 4 the reconstructed result has a good resolution and contrast to determine the expected area of the hemorrhage stroke's location.

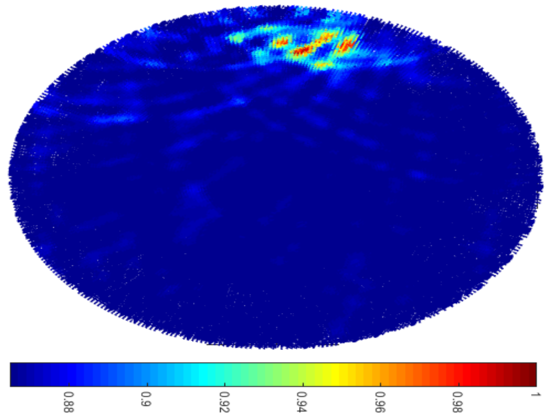


Fig. 4. Reconstructed image from confocal image reconstruction method with DAS beamforming techniques.

IV. THE PROPOSED POST-PROCESSING METHOD FOR SEGMENTATION AND CLASSIFICATION

In this section, we propose a new approach for automatic classification of the reconstructed images as normal or abnormal using Wavelet-Energy, PCA and SVM. Fig. 5 shows the flowchart of the proposed stroke detection and classification method. This automated CAD system, could be further used for classification of image with different pathological condition, types and disease status. The reconstructed image is the input for the proposed algorithm.

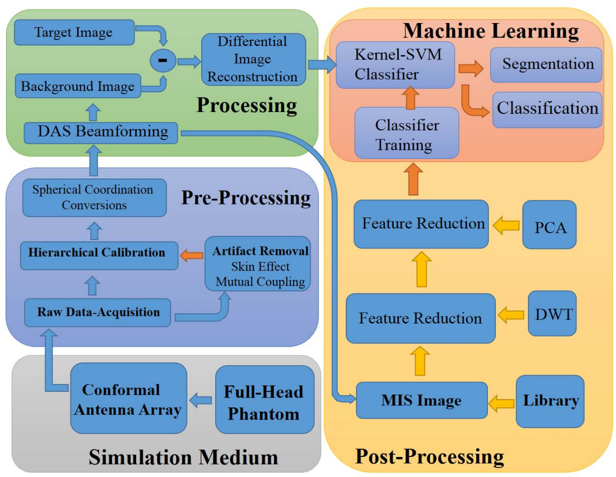


Fig. 5. Flowchart of the proposed stroke classification and segmentation method.

According to the proposed algorithm in Fig. 5, after image reconstruction, the first step in post-processing is feature extraction using 2D-DWT. For this purpose, the three levels of Haar wavelet decomposition greatly is applied as shown in Fig. 6 and which leads to reduce the input image size. The top left corner of the wavelet coefficients' image denotes the approximation coefficients of level 3, whose size is only $32\times124=3844$. The number of extracted features was reduced from $55\times 220=12100$ to 3844. However, it is still too large for calculation. Thus, PCA is used to further reduce the dimensions of features to a higher degree [14]. The curve of cumulative sum of variance versus the number of principle components is shown in Fig. 7. The variances versus the number of principle components shown in Fig. 7. It shows that only 29 principle components (bold font in table), which are only 0.7% of the original features, could preserve 88% of total variance.

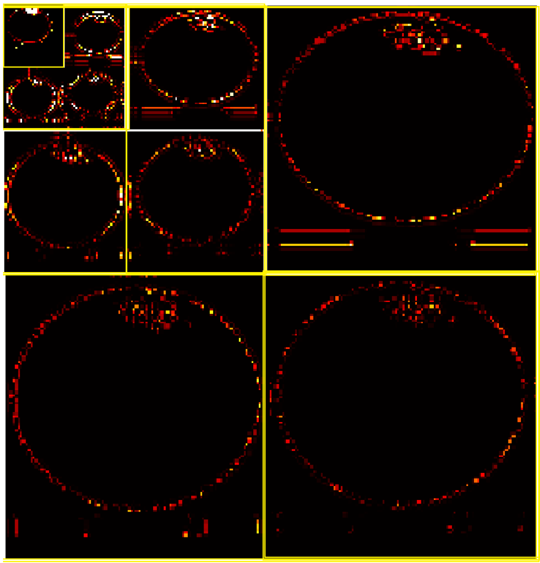


Fig. 6. The procedures of 3-level of the Haar wavelet coefficients (two-dimensional representation of discrete wavelet transform) for the reconstructed images from the head model with a hemorrhagic stroke target.

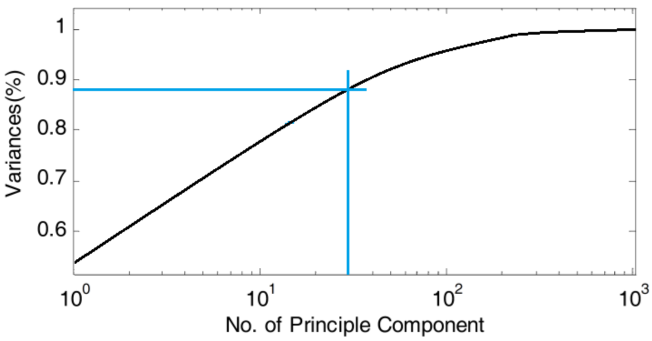


Fig. 7. Variances against number of principle components (x axis is log scale).

The support vector machine is a classification model whose basic model is defined as the linear classifier with the largest interval in the feature space [16]. With SVM, the original input space is mapped into a higher dimensional dot-product space called a feature space. In the feature space, an optimal hyperplane is found that maximizes the generalization property of the classifier. Fig. 8 illustrates the concept of maximum margin with bounding planes and support vectors. The decision boundary f(x)=w.z+b (the central line in Fig. 8) which is defined by a normal vector of the hyperplane and an offset. The margin is the minimal distance of any training points in the two classes (green circle represents the healthy case and red circle represents the stroke case) to the hyperplane. The support vectors are the training samples lying on the boundary hyperplanes of the two classes.

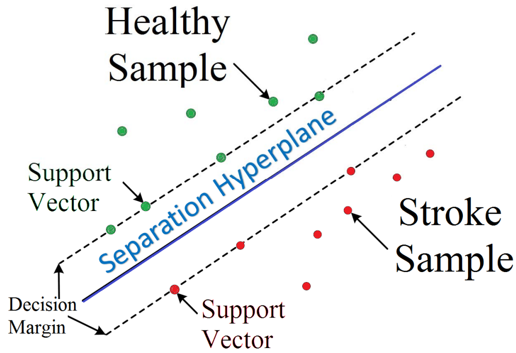


Fig. 8. Support vector machine (SVM) classifier:

In this step, our goal is to identify healthy and stroke samples by training a sample set of completed feature learning, which is a two-category problem. We can use classifiers such as SVM to figure out positive or negative cases. Consider the problem of separating the set of training data into two classes, where $z^i \in R_k$ is a feature vector and $y_i \in$ 1, +1 its class label. If we assume that the two classes can be separated by a hyperplane w.z+b=0 in some space H. Its classification decision function is:

$$f(z)=\mathrm{sign}(w.z+b) \tag{2}$$

The optimal hyperplane is the one, which maximizes the margin γ.

$$\gamma = y.f(z)/|||w|| \tag{3}$$

The optimization problem is:

$$\max_{w,b}\ \gamma \quad s.t\ y_i.f(z^i)>1 \tag{4}$$

The optimal values for w and b can be found by solving a constrained minimization problem, using Lagrange multipliers [17].

In order to train the SVM we generate the features by 2D-DWT feature extraction and PCA features reduction techniques. 2D-DWT is used as efficient feature descriptors. Then k-means clustering is implemented to construct two different clusters. The image of the cluster containing the head boundary is vectorized as the feature vectors. For training set, use the feature vectors to construct the SVM classifier. For testing set, we used the feature vectors to evaluate the SVM classifier.

The final step in the proposed algorithm is using the segmentation technique to separate out hemorrhage stroke region from MIS image. Segmentation highlights only the hemorrhage stroke region from reconstructed image. K-mean clustering is suitable for biomedical image segmentation, as the number of clusters is known for images [17]. The clustering is done by minimizing the Euclidean distance between centroid of cluster. The experiments demonstrate that the kernel SVM obtained more than 95% classification accuracy on the 16 images. In addition, the segmentation is applied for the reconstructed images. Here in this algorithm two segmentation methods are proposed, that are threshoding and watershed segmentation. Global thresholding is proposed in this algorithm, which gives a single threshold value to extract only hemorrhage stroke region from brain hemorrhage stroke MRI image. The bleeding region is highlighted by segmentation technique. Fig. 9 shows the original reconstructed image from confocal method and the segmented image. As shown in Fig. 9, to measure area of a hemorrhage stroke only this highlighted region is taken into consideration. The area of hemorrhage stroke is measured in terms of number of white pixels in that segmented image. The area is measured in terms of number of pixels. Because of segmentation, the hemorrhage stroke region looks like a white patch on image. The results showed that the proposed method gave better results than latest methods [17].

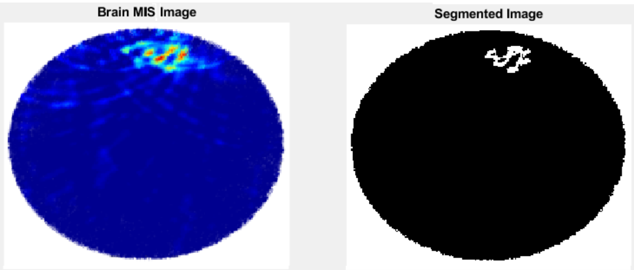


Fig. 9. Pattern recognition of the detected stroke using segmentation.

V. CONCLUSION

In this paper, an UWB microwave imaging system to detect and locate hemorrhage stroke in a full human head phantom using the time-domain data is presented. Additionally, the confocal method using DAS beamforming is used for image reconstruction. In the next step, we have developed a novel post processing methods including 2D-DWT based feature extraction, PCA based feature reduction and SVM based classification to distinguish between healthy and the brain with hemorrhage stroke. The DWT can efficiently extract the information from reconstructed image with little leakage. In addition, PCA reduced the 3844 dimensional search space to 30 dimensional search space, which is caused heavy computation burden and worsened classification accuracy. In the final step, we used SVM for classification between healthy and unhealthy cases. The experiments demonstrate that the kernel SVM obtained more than 95% classification accuracy on the 16 images. The results show that the developed imaging system has a good ability in detecting hemorrhage strokes in biological medium, even small targets of a few centimeters.

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