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FUZZY ANN BASED DETECTION AND ANALYSIS OF PATHOLOGICAL AND HEALTHY TISSUES IN FLAIR MAGNETIC RESONANCE IMAGES OF BRAIN

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A computational technique is proposed for the segmentation, detection and analysis of pathological tissues, healthy tissues and Cerebrospinal fluid (CSF) of brain with the help of FLAIR brain magnetic resonance images. Composite feature vectors are extracted from the blocks of size 4 × 4 pixels of intra-cranial brain image. Then using fuzzy C mean algorithm, clustering of feature vectors and segmentation of images are done for five regions tumor, edema white matter(WM), gray matter(GM) and CSF. Feature vectors comprise of empirically developed higher order wavelet function using Daubechies wavelet transform and statistical functions. Analysis of pathological regions and healthy tissue regions are done to see the complication of the disease. Segmentation result is validated and tested for 22 brain tumor patients. Training of artificial neural network using fuzzy back propagation algorithm is done for the detection of tumor, edema, WM, GM and CSF. The result using the composite feature vector developed is very satisfactory and mean square error is 2.58952 e-013.

Keywords: Segmentation, Fuzzy C Means Algorithm, Fuzzy Back Propagation Algorithm, Magnetic Resonance Imaging.

1. Introduction

Automatic brain tumor, edema and pathological segmentation from magnetic resonance images (MRI) are very important processes in medical imaging. It is a challenging task to find exact transition from healthy tissues to edema to tumor. Brain tumor management and treatment requires an accurate identification of tumor, edema and healthy tissues. Edema regions may be needed to be treated to reduce the risk of recurrence. Success of MRI in the treatment of brain pathologies is very encouraging but still diagnosis and locations of lesions are based on visual diagnosis using the available software by radiologists, making it prone to error. Researchers are continuously trying to develop a robust model for automatic brain tissue tissues segmentation and detection but a truly consistent model is yet to be established. In this work, effort is made to develop a computer-based technique for detecting tumor, edema, WM, GM and CSF so that human error can be reduced.

The brain Fluid Attenuated Inversion Recovery (FLAIR) Magnetic resonance (MR) images offer a valuable method to perform pre and post surgical evaluations. FLAIR images are widely accepted for brain diagnosis and are found very useful in the study and analysis of acute hemorrhage, in the diagnosis of intra cranial tumor, periventricular lesions, head injury, demyelinating diseases, such as multiple sclerosis, in the study of normal brain maturation etc. A FLAIR sequence is that which produces heavily T2 weighted and cerebrospinal fluid (CSF) nulled MR images. With this technique, subtle lesions near the CSF stand out against a back ground of attenuated CSF fluids as cerebrospinal fluid (CSF) appears dark and most lesions, tumors and edematous tissues appear bright, as shown in figure1.

Most of the methods used in MR imaging are for the segmentation of tumor only. However the knowledge of edema is very important as cerebral edema contributes strongly to symptoms associated with brain tumors. FLAIR images provide better discrimination between tumor and edema than T2 weighted and T1 weighted images. Analysis of segmented images is done for finding out spread of pathological tissues and criticality of disease, which is very important and critical for therapy planning, treatment and surgery point of view.

In recent years the MR image segmentation techniques used by researchers are multi spectral analysis, fuzzy clustering techniques classical pattern recognition methods, rule based system and through ANN [1-4].

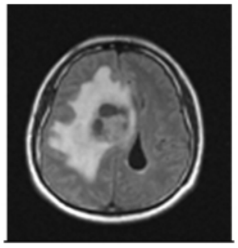

Fig.1: FLAIR image

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In all above-mentioned work researchers concentrated on the segmented tumor region only using T1, T2 and PD images. But the knowledge of edema is very crucial for the therapy planning, diagnosis, surgery and management of tumor.

Wavelets are mathematical tools which have found more and more applications in digital image processing, compression, segmentation and feature detection in last one decade. Many authors used properties of wavelet transform for the segmentation of images. Classification of textured and non textured images and targets using region segmentation, wavelet coefficients and multi-resolution theory was done by several authors [5-7].

Now in recent years FLAIR images are found to be very useful and accepted widely in research area for the analysis and diagnosis of brain. Researchers use FLAIR images to describe clinical applications [8-12] and for the study of intra cranial tumors for more than 30 patients, by Tsuchiya et al [8]. Hirota, Ishihara et al used delay Post Contrast FLAIR image [11] for depicting meningeal carcinomatosis that was visualized more clearly on post contrast MRI. For segmenting healthy and pathological tissues, different techniques using FLAIR and contrast enhanced FLAIR images are used by various researchers.

Now in last one and half-decade research works have been done for the detection of tumor and edema together [13-17]. Mechanism of tumor related brain edema was studied by Stummer [13] and Baggenstos et al. [14].Cai et al done probabilistic segmentation of brain tumors based on multi-modality magnetic resonance images [15]. Prastawa etal segmented tumor and edema using T2 MR images [16].

In my work, FLAIR images are used to detect tumor and edema (pathological tissues), white matter and gray matter (healthy tissues) and CSF using empirically developed functions of higher order of Daubechies wavelet transform and statistical parameters as the elements of feature vector. The segmentation result using the newly developed composite feature vector in this paper is very satisfactory and mean square error is very low.

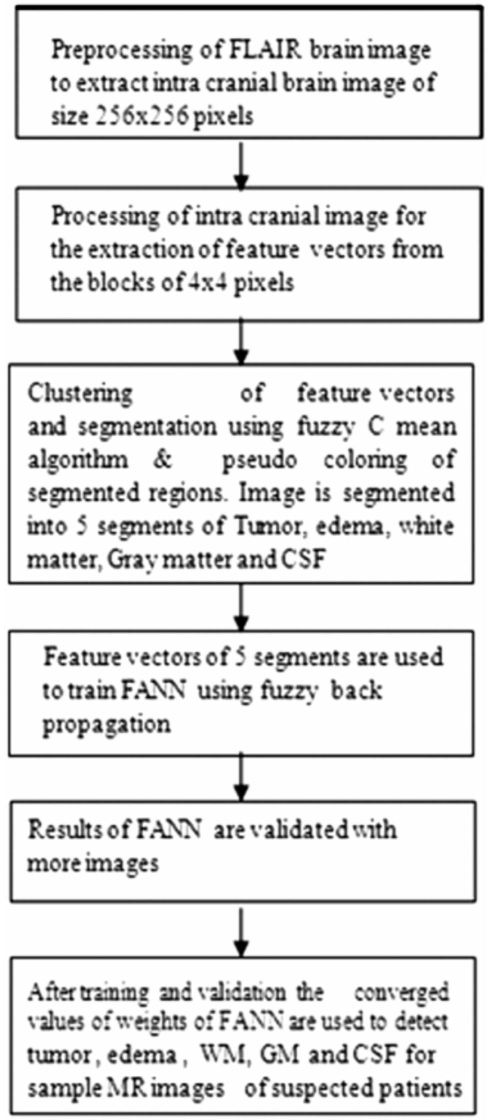

Fig.2: Diagram to Show Flow of Process

2. METHODOLOGY

In this paper higher order empirical functions of wavelet transform and statistics are used as elements of feature vectors of blocks of brain FLAIR images.

The flow diagram of work is as shown below in figure 2.

2.1 Preprocessing

Brain MR images are preprocessed and to increase contrast, median filter of 9 × 9 is applied. Then intra cranial brain is extracted from the original image. This is required because removing extra cranial tissues such as skull; eyes etc. make segmentation easy and eliminates possibilities of false segmentation. In this work intra-cranial brain is extracted with the help of MATLAB image processing software.

2.2 Feature Vector Extraction From Blocks of 4 × 4 Pixels of Images

For extraction of feature vectors intra cranial images are processed block wise. Whole image of size 256 × 256 is partitioned into blocks of 4 × 4 pixels and using MATLAB program feature vectors are extracted corresponding to each block. Feature vectors comprises of 4 features, one parameter is higher order function related with pixel values of the block, and other three features are higher order function of 2 × 2 wavelet coefficients of horizontal, diagonal and vertical frequency bands of blocks. A wavelet transform divides an image into several simpler images at a different scale and can significantly reduce the dimension of the image as the level of the transform increases. After a one level wavelet transform 4 × 4 block is decomposed into four frequency bands of 2 × 2 coefficients, out of which one low frequency band (LB) gives approximate information and three high frequency bands (HB, VB, DB) give detail information in horizontal, vertical and diagonal directions.

In figure 3 one level Daubechies wavelet transform of brain image is shown. In figure 3 the low frequency part is displayed on the upper-left corner, horizontal sub image on upper right corner, vertical sub image on lower left corner and diagonal sub image on lower right corner are displayed. In this work, coefficients of high frequency bands are used to derive features of feature vector. The motivation for using the features extracted from high frequency bands is that they reflect texture properties and useful in segmentation process.

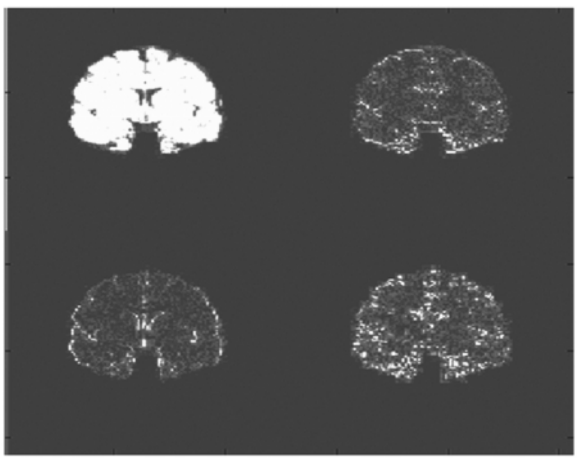

Fig.3: Brain Image Decomposes Into Four Sub Images After One Level Daubechies Wavelet Transform

The feature vector Fi for each block $i \in I$, where I is 2D brain image, is defined as

$$F_i = [\, f_i^{(1)}, f_i^{(2)}, f_i^{(3)}, f_i^{(4)}]$$

Where $f_i^{(1)}$, $f_i^{(2)}$, $f_i^{(3)}$, $f_i^{(4)}$ are empirically developed elements of feature vector. Suppose in one block, pixel values are P_1 to P_{16}. Then the first element, which is higher order empirical function, is related with pixel values of the pixels of block.

$$f_i^{(1)} = \{1/16(P_1^5 + P_2^5 + P_3^5 + \ldots\ldots + P_{16}^5)\} \quad (1)$$

Other three features are higher order function of 2 × 2 wavelet coefficients of horizontal, diagonal and vertical frequency bands of blocks, which are also empirical functions, developed by authors of this paper. After applying one level Daubechies transform, blocks of 4 × 4 pixels are decomposed into four sub images. In this work we have considered coefficients of horizontal band H1, H2, H3, H4, coefficients of diagonal band D1, D2, D3, D4 and coefficients of vertical band V_1, V_2, V_3, V_4 to compute higher order wavelet functions $f_i^{(2)}$, $f_i^{(3)}$, and $f_i^{(4)}$ as in equations (2), (3) and (4) respectively.

$$f_i^{(2)} = \{1/4\,(H_1^6 + H_2^6 + H_3^6 + H_4^6)\}\text{^}1/2 \quad (2)$$

$$f_i^{(3)} = \{1/4\,(D_1^6 + D_2^6 + D_3^6 + D_4^6)\}\text{^}1/2 \quad (3)$$

$$f_i^{(4)} = \{1/4\,(V_1^6 + V_2^6 + V_3^6 + V_4^6)\}\text{^}1/2 \quad (4)$$

In this work 2D analysis of brain image of size 256 × 256 is done. There are total 4096 feature vectors corresponding to 64 × 64 = 4096 blocks, each of size 4 × 4 = 16 pixels. Corresponding to each block there is one feature vector that describes its attributes in terms of four parameters. Total 4096 feature vectors clustered into five different clusters of tumor, edema, WM, GM and CSF by fuzzy C-Mean algorithm. Clustered feature vectors are used to form segmented image of original size 256 × 256.

2.3 Clustering Using Fuzzy C-Mean Algorithm

Clustering algorithms are used to place similar patterns in the same cluster. The main difference between fuzzy clustering and other clustering techniques is that it generates fuzzy partitions of the data instead of hard partitions. In medical diagnosis systems, fuzzy C-means algorithms give the better results than hard- k means algorithm. Fuzzy clustering methods can be important supportive tool for the medical experts in diagnostic. In our paper clustering module is based on the Fuzzy C-Means algorithm (FCM). FCM is a fast algorithm and we developed a program in MATLAB that groups the feature vectors of image into 5 clusters using FCM.

Take x_k is 4-dimensional feature vector and cluster center v_i , n = 4096 is the number of feature patterns, C = 5 is the number of clusters. Here in the paper there is a set of 4096 data patterns,

$X = x_1; \_\_\_; x_k; \_\_\_; x_{4096};$, The algorithm minimizes the objective function, J(U; V):

$$J(U,V) = \sum_{k=1}^{4096} \sum_{i=1}^{5} u_{ik}^{m} d^2(x_k, v_i)$$

Where x_k in this program is the k-th 4-dimensional feature vector, v_i is the prototype of the center of cluster i, u_{ik}^m is the degree of membership of x_k in the i-th cluster, m is a weighting exponent on each fuzzy membership, $d(x_k,v_i)$ is a distance measure between feature vector.

The objective function J(U; V) is minimized via an iterative process in which the degree of membership u_{ik} and the cluster centers v_i are updated as per equations (5) and (6) respectively:

$$u_{ik} = 1/1 + \sum_{j=1}^{5} (di_k / di_j)^{2/(m-1)} \quad (5)$$

$$V_i = \sum_{k=1}^{n=4096} u_{ik}^{m}\, x_k / \sum_{k=1}^{n=4096} u_{ik}^{m} \quad (6)$$

Where for all i $u_{ik \text{ satisfies:}}$ $u_{ik} \in [0,1]$ and for all k

$$\sum_{i=1}^{5} u_{ik} = 1 \text{ and } 0 < \sum_{k=1}^{5} u_{ik} < n = 4096$$

2.4 Artificial Neural Network Trained with Fuzzy Back Propagation Algorithm

An artificial neural network (ANN) is used for structure identification. MR images are large data set with an important number of independent variables and complex relationship that usually show nonlinear characteristics. ANN is good tool to analyze such MR data and classifying different tissues in terms of texture, intensity and contrast. ANN have been taught to mimic the decision making process needed to perform the task of identification. The ANN was given the prior knowledge and expertise. The program is made in MATLAB and algorithm used to train ANN is the fuzzy back propagation algorithm (FBPA). Fuzzy BP is hybrid architecture, which maps fuzzy inputs to crisp outputs. In this work fuzzy back propagation network (FBPN) is three-layered feed forward network having input layer, hidden layer and output layer. Both input and hidden layer are using fuzzy neurons. In this work in the fuzzy neuron, both input and weight vector are represented by triangular type of LR-type fuzzy numbers and can be represented as $(m, \alpha, \beta)_{LR}$. Here m is called mean value and α and β are called left and right spreads respectively [18]. The functioning of FBPN proceeds in two stages training and inference.

3. Implementation

3.1 Image Data

MR brain data is available from 1.5 Tesla SIEMENS MRI machine. MRI brain scans of 37 patients (many slices per patient) are available. For all patients several slices of T1, T1 contrast, T2, FLAIR images for axial, sagittal, coronal views are available. For this work FLAIR MRI images in coronal plane are used with TI= 2300, TR = 8000 and TE = 120 in all acquisition. Input data for fuzzy back propagation feed forward network are feature vectors containing four parameters, which are higher order functions developed by authors of this paper.

3.2 Segmentation

The software developed in this work in MATLAB, clusters 64 × 64 = 4096 input feature vectors of image into 5 different clusters of tumor, edema, white matter, gray matter and CSF. Clustered feature vectors are used to form segmented image of original size 256 × 256. Segmentation result after pseudo coloring is shown in figure 4 for five patients showing healthy tissues, pathological tissues and CSF. In figure 4 block wise reconstructed segmented image with 5 segments showing tumor (orange) and edema (green), white matter (blue), gray matter (purple) and CSF & background (black).

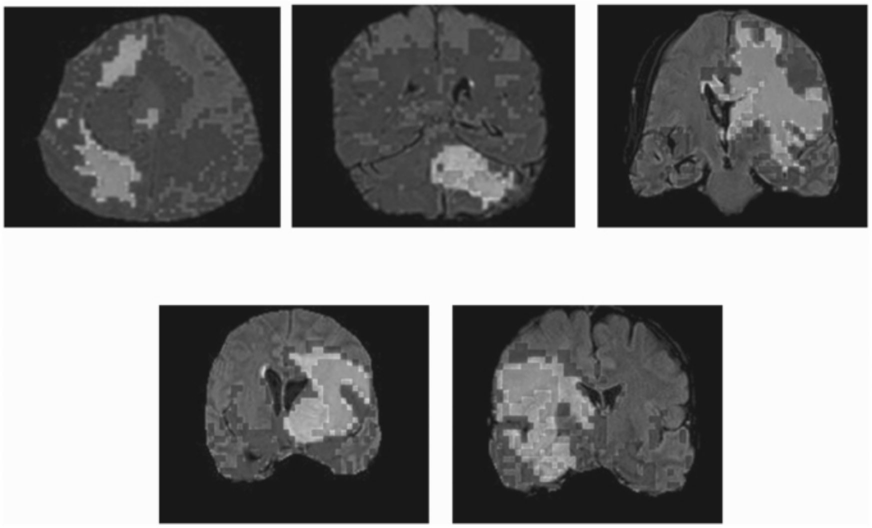

Fig. 4: Segmented Brain Image

3.3 Analysis of Segmented Images

Analysis of segmented images for 5 patients is done for finding out criticality of disease. Percentage of tumor and edema tissues in intra cranial brain image is calculated and hence percentage of total pathological tissues can be found. Knowledge of spread of pathological tissues in brain is very important and critical for therapy planning, treatment and surgery point of view. Table1 is showing details of tumor, edema and healthy tissues for 5 patients. From the table, spread of tumor and edema can be seen for the patients and planning for treatment can be done accordingly.

Table 1
Details of Tumor, Edema and Healthy Tissues for 5 Patients.

Patient	Pixels in intra cranial brain image	Tumor Tissues (tu)		Edema Tissues (ed)		Pathological Tissues (tu + ed)		Healthy Tissues	
		Pixels	%	Pixels	%	Pixels	%	Pixels	%
Patient 1	15,990	802	5.01	932	5.82	1,734	10.84	14,256	89.15
Patient 2	17,634	422	2.39	1,836	10.41	2,258	12.80	15,376	87.19
Patient 3	17,489	2,090	11.95	2,621	14.98	4,711	26.93	12,778	73.06
Patient 4	12,336	972	7.87	1,399	11.34	2,371	19.22	9,965	80.779
Patient 5	14,967	1,224	8.177	3,048	20.36	4,272	28.54	10,695	71.45

3.4 ANN Structure, Training and Validation

Our aim is to detect pathological tissues tumor and edema and healthy tissues. With the knowledge of feature vectors of tumor, edema, WM, GM and CSF as inputs, training of ANN is done using fuzzy back propagation algorithm (FBPA). Features of all blocks of the image are extracted and stored for training purpose. These training blocks are taken from the brain images of 15 different patients. Some of the extracted feature vectors of tumor, edema, white matter, gray matter and CSF are shown in Table 2. The results of fuzzy ANN are then validated with 10 images. After training and validation, fuzzy ANN is used to identify tumor, edema, healthy tissues and CSF in the images of 12 different patients and verified by radiologists.

FBP ANN structure is a three-layered architecture consisting of input layer, hidden layer and output layer. Fuzzy ANN is trained to detect tumor, edema, white matter, gray matter and CSF together. In fuzzy ANN structure both input and hidden layers consists of 5 fuzzy neurons (4 for features and 1 for bias) and output layer consists of 5 neurons (for tumor, edema, white matter, gray matter and CSF). Number of input-hidden weights are 25, Number of hidden-output weights are 25 and hence total number of weights in the network is 50.

Table 2
Samples of Extracted Feature Vectors From Tumor, Edema, WM, GM and CSF Blocks

FV No	Tissue Type	Horizontal Wavelet Function	Diagonal Wavelet Function	Vertical Wavelet Function	Higher Order Statistical Function
FV1	Tu	0.0014	0.0003	0.0125	0.0867
FV2	Ed	0.0103	0.0093	0.0035	0.0934
FV3	WM	0.0181	0.0013	0.087	0.0889
FV4	WM	0.0355	0.0008	0.0065	0.0908
FV5	GM	0.0032	0.0004	0.0465	0.0363
FV6	Ed	0.0062	0.0009	0.149	0.1038
FV7	Tu	0.0547	0.0004	0.002	0.0373
FV8	CSF	0.0094	0.0055	0.014	0.0632
FV9	GM	0.0055	0.0012	0.0034	0.0078
FV10	CSF	0.0059	0.0272	0.139	0.0810

4. Result and Conclusions

For implementing image segmentation, computer program has been developed using MATLAB. It takes about 45 seconds on average to segment a 256 × 256 image in 5 segments using MATLAB 7.0 software on a Pentium 4, 3GHz with XP operating system. After that the time spent in the neural network training using MATLAB to detect 5 segments is 53 seconds in 2000 iterations only. The performance of the network is derived which is as low as 2.58953e-013 as shown in Figure 5. Block wise segmentation improves the computational speed of the segmentation process. BPA based ANN offers promising results in the task of classifying brain tissues. Neural network training is done for pathological tissues, healthy tissues and for CSF and for that feature vectors are taken from all 5 segments. Correct classification of tissues depend mainly on the local texture values, therefore it is necessary to include features that can measure this index. It is for this reason that parameters of feature vectors are statistical quantities and parameters related with wavelet coefficients of high frequency bands. Four higher order features of feature vector are generated empirically by authors that reflect texture properties and pixel value analysis of different segments of images and gives better segmentation result as compared to previous work.

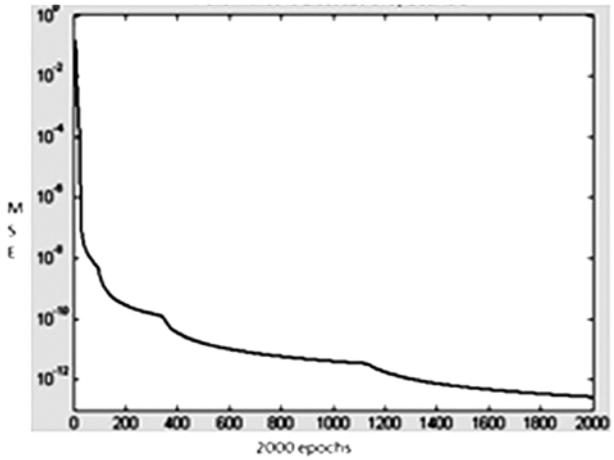

Fig.5: Performance Measure for Fuzzy ANN Trained to Detect Tumor and Edema

This work presents automatic segmentation of tumors, edema, healthy tissues and CSF. The FANN is trained with fuzzy back propagation algorithm and is tested with the whole image. It is identifying tumor, edema, white matter, gray matter and CSF very accurately for 12 patients and verified by radiologists. The results in this work are very encouraging and computational speed and efficiency is satisfactory. For test patients input samples and corresponding outputs of simulated FANN are tabulated in tables 3(a) and 3(b) respectively and are found to be consistent with the radiologists' findings.

Table 3(a)
Test Input Patterns

Feature Vector	Horizontal Wavelet Function	Diagonal Wavelet Function	Vertical Wavelet Function	Higher Order Statistical Function
FV1	0.0412	0.0002	0.0235	0.0530
FV2	0.0040	0.0008	0.0093	0.2496
FV3	0.0164	0.0009	0.0053	0.0260
FV4	0.0062	0.0010	0.035	0.0573
FV5	0.0347	0.0055	0.0004	0.0660
FV6	0.0107	0.0023	0.0012	0.0623
FV7	0.0081	0.0678	0.0789	0.1695
FV8	0.0188	0.0084	0.0088	0.1173
FV9	0.0114	0.0080	0.0115	0.0547
FV10	0.0731	0.0492	0.0044	0.1202

Table 3(b)
Corresponding Outputs of Simulated FANN for the Inputs in Table 3(a).

Feature Vector	Tumor	Edema	White Matte	Gray Matter	CSF	Detected Type Tissue
FV1	0.9912	2.356 e-006	3.289 e-005	5.78 e-009	7.983 e-006	Tumor
FV2	4.523 e-007	1	5.634 e-006	4.658 e-009	2.117 e-010	Edema
FV3	3.225 e-008	1.721 e-006	1.65 e-009	0.99956	4.524 e-011	Gray Matter
FV4	3.451 e-007	5.462 e-008	2.498 e-006	1	6.483 e-009	Gray Matter
FV5	3.008 e-008	2.195 e-008	0.99934	3.667 e-006	4.08 e-009	White matter
FV6	1	1.453 e-009	6.231 e-009	3.649 e-007	2.005 e-009	Tumor
FV7	2.306 e-008	3.05 e-009	2.34 e-008	5.076 e-006	1	CSF
FV8	8.321 e-007	7.572 e-009	6.486 e-006	2.119 e-007	0.99835	CSF
FV9	3.012 e-006	0.98994	4.011 e-006	4.73 e-008	2.451 e-011	Edema
FV10	1.129 e-007	3.056 e-008	0.9965	2.106 e-008	6.325 e-009	White Mater

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