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Bandelet Transform With Predictive Entropy Encoding for 4D FMRI Image Compression

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ABSTRACT
The main idea behind this compression scheme, which uses Bandelet transform, fuzzy thresholding of the Bandelet coefficients and arithmetic coding is to compress 4D functional Magnetic Resonance Imaging (fMRI) images. Bandelet thresholding is expressed as fuzzy wavelet thresholding using the standard sigmoid function as the membership function. Lossless arithmetic entropy coding and predictive entropy encoding of the thresholded coefficients are performed. Decompression is done by Inverse Bandelet Transform to obtain the reconstructed image. Since lossless compression of 4D medical images is still a new area of research, 3D and 2D lossless compression algorithms are often used to compress volumes or slices independently. Current 2D and 3D compression methods use mainly wavelet transforms or prediction coding to decorrelate the data and improve the compression performance. However, these compression methods fail to exploit redundancies in all four dimensions. Hence, efficient compression methods are needed for 4D medical images. In the proposed research work, new lossless compression methods for 4D functional magnetic resonance images (fMRI) will be proposed which are based on bandelet and contourlet transforms for exploiting the redundancies in all dimensions of 4D FMR images. In bandelet transform; to capture the anisotropic regularity of edge structures apart from capturing regularity information from smooth regions. In contourlet transform, there are two stages: a Laplacian pyramid, followed by Directional filter bank. The Laplacian pyramid is used to capture the point discontinuities, and Directional filter bank is used to link point discontinuities and to give directional information to the contourlet transform. In the proposed research work, the aim is to exploit the redundancies in all dimensions of 4D FMR images; using a bandelet and contourlet transforms.

Keywords: Bandelet transform, Fuzzy thresholding, inverse bandelet transform and 4D fMRI, Predictive entropy encoding and Arithmetic entropy encoding

1. INTRODUCTION
The novelty behind the detection of brain tumor is by quantifications from a particular MRI scan of the human brain using digital image processing. The area of the tumor from the MRI images is identified using automatic extraction. The main difficulties in field of automatic tumor segmentation are related to the fact that the brain tumors are very heterogeneous in terms of shape, color, texture and position as they often deform other nearby anatomical structures. A healthy brain has a strong sagittal symmetry that is weakened by the presence of the tumor. The comparison between the healthy and ill hemisphere, considering that tumors are generally not symmetrically placed in both the hemispheres, was used to detect the anomaly. Digital image processing allows a much wider range of algorithms to be applied to the input data and can avoid problems such as the build-up of noise and signal distortion during processing. Experiments demonstrate that the method can successfully achieve segmentation of MR brain images to help pathologists distinguish exactly the lesion size and region. The classification efficiency of the algorithms is also validated**.**

A major goal of fMRI measurements is the localization of the neural correlates of sensory, motor and cognitive processes. The term “brain mapping” is often used to refer to this goal of relating operations of the mind to specific areas and networks in the brain. Another major goal of fMRI studies is the detailed characterization of the response profile across experimental conditions for known Regions-of-Interest (RoIs). In this context, the aim of conducted studies is often not to map new functional brain regions but to characterize further how a known specialized brain area responds to differences in experimental conditions of interest (RoI-based analysis). This chapter describes the first analysis steps that are usually conducted to reach these goals. The described analysis steps include data preprocessing such as head motion correction and filtering. In order to perform whole brain analysis with the data from multiple subjects (group analyses), the data is usually transformed into a common, normalized, space, which involves the co-registration of functional and anatomical data sets, an anatomical brain normalization step and the transformation of functional data into the normalized space resulting in Volume Time Course (VTC) data files. After completion of these steps, statistical single subject and group analyses can be performed.

2. OBJECTIVES OF THE PROPOSED WORK

The following are the objectives of the proposed work for implementation of bandelet transform for compression of fMRI images.

- To reduce the human effort for testing and treating of diseases
- Fuzzy set theory and Fuzzy logic offers to be a powerful tool to represent and process the knowledge base as IF-THEN rules.
- Using fuzzy set theory, bandelet thresholding can be expressed as fuzzy wavelet thresholding
- The standard S-membership function is used as the membership function
- Computation of the frequency histograms for the bandelet coefficients is done to find the frequency of occurrence of the intensity values
- The threshold range is adjusted from ‘0’ to the maximum value and in each position the amount of fuzziness is computed.
- The fMRI data set consists of a time-series of voluminous data as explained earlier. Each point in an fMRI data set has an unique coordinate in 4D space where (x, y, z) are the spatial coordinates and ‘t’ is the time coordinate.
- Compression of the fMRI images using arithmetic and predictive encoding

3. LITERATURE SURVEY

Magnetic Resonance Imaging (MRI) is widely applied to the examination and assistant diagnosis of brain tumors owing to its advantages of high resolution to soft tissues and none of radioactive damages to human bodies. Integrated with medical knowledge and clinical experience, the experienced doctors can obtain the sizes, locations, shapes and other pathological characteristics of brain tumors according to the information in MRI images to make scientific and reasonable therapeutic treatment. Because there are several MRI examinations for every patient in the whole therapeutic treatment, each of which can give 3-dimensional data in multiple sequences, it is a large amount of data to be dealt with for the doctors. Long time of hard work will inevitably lead to mistakes in the diagnosis of the tumor contours for the doctors. Moreover, it is subjective for the doctors to determine the state of the diseases according to their medical knowledge and clinical experiences. Therefore, developing an automatic or a semi-automatic computer-aided diagnosis system is meaningful in real medical treatments, which can release the workload of doctors and improve the accuracy by giving objective results. This problem is a hot point in the research field of biomedical engineering and a lot of algorithms have been proposed to try to solve it. But unfortunately it is still unsolved due to the limitations of low accuracy, efficiency, applicability and robustness of existing algorithms.

The brain image analysis [12] process is discussed from the viewpoint of MRI brain imaging types which are listed in Table 1.

Table 1. MRI brain images analysis methods comparison

S. No	Application	Pros	Cons	Results
1	MRI brain segmentation [12]	Has application to MRI as well as to EEG and MEG	-	It has been shown through results that the technique handles MRI segmentation in an effective way.
2	MRI volume visualization [13]	Handles both 2D and 3D data	-	The results show that the method gains a powerful ability of structural manipulation and volume visualization
3	Segmentation of MRI images [14]	Feature segmentation of even noisy images	Difficult formulation	Results of this technique show that it is better, fast and accurate as compared to other algorithms
4	Segmentation of MRI medical images [16]	The advantage is that the proposed method is very fast in segmentation and automatic as well	Less accurate with noisy images	Average differences are 1. 7% and 2. 7%
5	MRI images registration of medical sector [17]	If there is a picture with less information, it will handle it	-	Results show that the proposed method is better for dealing missing information pictures
6	MRI brain segmentation in medical sector [20]	Advantage of this method is that it can segment and detect brain as well as contour	Limitation is that calculation is difficult for contour detection	Proposed method shows better results for contour and brain detection as well as for segmentation
7	MRI brain sector [18]	Advantage is that it is more robust as compared to	Limitation is that data is complex because of 3D	Improved results are obtained through 3D

		the individual implemented techniques	images	segmentation of MRI Brain Images
8	MRI brain sector [19]	Advantage of this method is that it is fast and easy to understand	-	The proposed method is tested and compared with ordinary algorithms and it shows better results.
9	Brain images of MRI [21]	Advantage of this method is that it is fast and easy to understand	Limitation is that it has greater tile of computations	The proposed method shows better results as compared to other methods and algorithms.
10	Medical MRI brain department [22]	Advantage of the work is that it does not require any manual data	Limitation of this method is that it shows less accurate results on adult brain images	The suggested technique gives more accurate experimental results in comparison with existing methods
11	MRI brain department [23]	It has greater speed and accuracy and it is simple as well	Limitation is not mentioned	Results show that the method proposed is fast and more accurate as compared to algorithms already existing
12	MRI abdominal images department [24]	Advantage is that it is fast	-	The proposed technique gives more precise and reliable results
13	3D segmentation of medical images [25]	This method is very efficient to volume estimation and segmentation	It shows less accuracy if quality of image is low	Experimental results show that novel method is more accurate rather than the ordinary methods
14	Medical sector [26]	Advantage is that it is used for both manual and automatic segmentation	Limitation of this method is that it has very complex calculations	Results show that the segmentation procedure added with the volume visualization has strong ability to segment brain
15	Medical sector [27]	Advantage is that it segments the brain from even noisy images	Limitation is that it involves different algorithms and thus it is complex	The extensive experiments are conducted to validate the results and proposed method shows better results

4. PROPOSED ARCHITECTURE

Data storage and sharing is difficult for these sensors due to the data inflation and the natural limitations, such as the limited storage space and the limited computing capability. Since the emerging cloud storage solutions can provide reliable and unlimited storage, they satisfy to the requirement of pervasive computing very well.

Magnetic Resonance Imaging (MRI) is the state-of the-art medical imaging Technology which allows cross sectional view of the body with unprecedented tissue contrast. MRI is an effective tool that provides detailed information about the targeted brain tumor anatomy, which in turn enables effective diagnosis, treatment and monitoring of the disease. Its techniques have been optimized to provide measures of change within and around primary and metastatic brain tumors, including edema, deformation of volume and anatomic features within tumors, etc. Information extracted from MRI provides a digital representation of tissue characteristic that can be obtained in any tissue plane. The images produced by an MRI scanner are best described as slices through the brain. MRI has the added advantage of being able to produce images which slice through the brain in both horizontal and vertical planes. This makes the MRI-scan images an ideal source for detecting; identifying and classifying the right infected regions of the brain, shown in Figure 1.

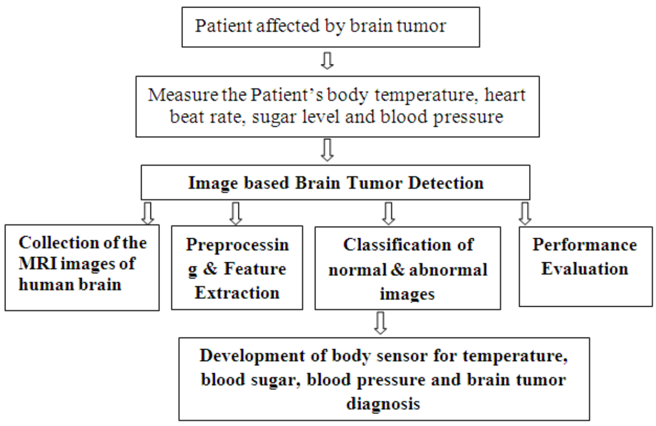


Figure 1. Collection of patient's biochemical parameter and MRI for validation

5. METHODOLOGY FOR IMPLEMENTATION OF BRAIN TUMOR DETECTION FROM fMRI

Basically different brain image types are MRI, CT, PET, and EEG/MEG. In this section we will analyze MRI methods and techniques that have been proposed in the perspective of brain image analysis. The first paper in this regard is a MRI brain segmentation method [12]. The procedure presented is for finding brain and contours. Also genuine computation form for EEG and MEG investigation is proposed. The work proposed in [13] is a 3D volume information segmentation centered on 2D image segments. By utilizing the customer presented image mask containing the concerned regions or structural data, the half automatic segmentation method is able to produce segmented fresh volume dataset and regional data. The object centered volume apparition procedure is capable of using this segmented dataset and regional data to carry out structural centered treatment and visualization. The method described in [14] presents the geometric active contour models for detecting the edges and segmentation [15] of MRI and CT images. Method defined is based on feature matrices and then added to the novel snake paradigm. Another automatic brain segmentation of MRI images is addressed in paper [16]; proposed method follows two steps: i) initial model is created first ii) secondly that model deformation to map the precise contour of brain. Automatic segmentation is thus performed by following these two steps. The method described in [17] is the process of registration of brain images. The images are multimodal of MRI and SPECT. This was the big problem because of non availability of any land mark. To overcome this problem, the method uses the anatomic invent brain properties. The method is also presented for missing information i. e., pathological cases. A hybrid method in [18] is introduced for brain segmentation in 3D MRI images. Fuzzy region growing and edge detection is introduced. The proposed technique combines the edge detection method and region growing method. In [19] a novel system is presented to segment automatically from the MRI brain images. Different algorithms are used to extract different types of data. Proposed graph cut atlas based method uses that prior data or information and automatically calculates the atlases and boundaries from the image.

5. 1 Implementation of Bandelet transform for processing 4D fMRI Brain images

5. 1. 1. Bandelet transform with Arithmetic Entropy coding

Step 1: The 2D image is forward bandelet transformed to obtain the bandelet coefficients. Let the coefficients of 2D discrete bandelet transform of image be represented. Orthogonal bandelet use an adaptive segmentation and a local geometric flow and are thus able to capture the anisotropic regularity of edge structures.

Step 2: To perform fuzzy bandelet thresholding as discussed in the previous section. The standard-S membership function is selected.

- ✓ The histogram of the bandelet coefficients is computed
- ✓ The threshold (T) is moved and in each position the linear index of fuzziness is computed
- ✓ The threshold where the linear index of fuzziness is minimum is used as the threshold

The bandelet coefficients which are greater than T remain as such and the remaining coefficients are set as zero. Let be the fuzzy bandelet thresholded image.

Step 3: To perform lossless arithmetic entropy coding of the thresholded coefficients. Decompression is the inverse of the compression stage. Arithmetic decoding is done to extract the fuzzy thresholded bandelet coefficients, Next step is to perform inverse bandelet transform to obtain the reconstructed image. The entire process is illustrated in Figure 2(a).

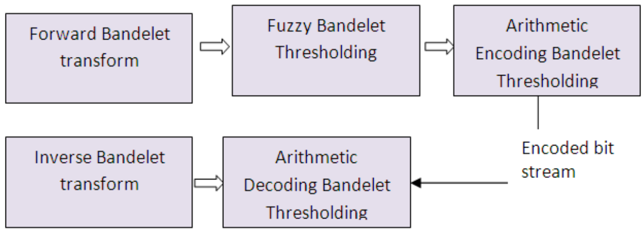


Figure 2(a). Block diagram for implementation of Bandelet transform with Arithmetic entropy encoding

5. 1. 2. Bandelet transform with Predictive Entropy coding

Step 1: The 2D image is forward bandelet transformed to obtain the bandelet coefficients. Let the coefficients of 2D discrete bandelet transform of image be represented. Orthogonal bandelet use an adaptive segmentation and a local geometric flow and are thus able to capture the anisotropic regularity of edge structures.

Step 2: To perform fuzzy bandelet thresholding as discussed in the previous section. The standard-S membership function is selected.

- ✓ The histogram of the bandelet coefficients is computed
- ✓ The threshold (T) is moved and in each position the linear index of fuzziness is computed
- ✓ The threshold where the linear index of fuzziness is minimum is used as the threshold

The bandelet coefficients which are greater than T remain as such and the remaining coefficients are set as zero. Let be the fuzzy bandelet thresholded image.

Step 3: To perform lossless AI based entropy coding of the thresholded coefficients. Decompression is the inverse of the compression stage. Arithmetic decoding is done to extract the fuzzy thresholded bandelet coefficients, Next step is to perform inverse bandelet transform to obtain the reconstructed image. The entire process is illustrated in Figure 2(b).

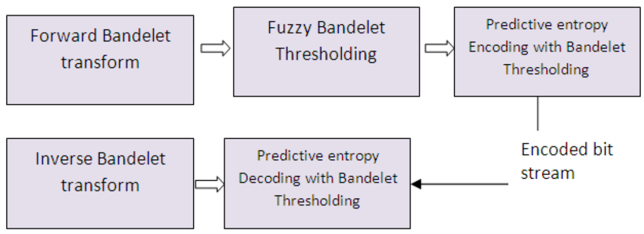


Figure 2(b). Block diagram for implementation of Bandelet transform with Predictive entropy encoding

5. 2 K-Means Clustering
The K-means clustering is an algorithm to group objects based on attributes into numbers of groups where k is a positive integer. The Clustering is done by minimizing the Euclidean distance between data and the corresponding cluster centroid. Thus the purpose of k-means clustering is to cluster the data. K-means algorithm is one of the simplest partitions clustering method. The flowchart is shown in Figure 3.

5. 2. 1 Algorithm

1. Give the no of cluster value as k
2. Randomly choose the k cluster centers
3. Calculate mean or center of the cluster
4. Calculate the distance between each pixel to each cluster center
5. If the distance is near to the center then move to that cluster
6. Otherwise move to next cluster

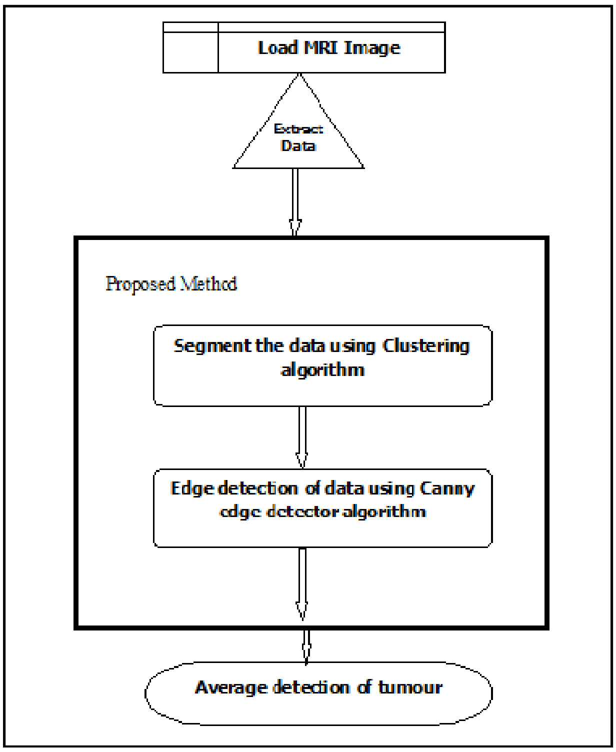


Figure 3. Flowchart for K-means clustering Algorithm

6. RESULTS AND DISCUSSION
The 4D fMRI data set (brain images) contains nearly 87 images which included both normal and abnormal categories. This set is subdivided into training and testing data set. The training set includes nearly 51 images and the remaining 36 images are used for testing the validity of the algorithm. The results of the proposed bandelet transform are compared with the conventions clustering methods.

6. 1 Results for Implementation of K-means Clustering Algorithm for Brain tumor detection
The first step in the segmentation is Thresholding the input image which is nothing but converting the input image into Black & White image or Binary image. The Figure 4 is the threshold image. The pixel value from 0 to 200 signifies 0 and is shown by white region. The pixel value from 200 to 255 signifies 1 and is shown by black region. The Figure 5 is the image obtained from FCM clustering in which the tumor can be seen clearly. To get this FCM clustered image a number of layers has been segmented to get the final image. The set of clusters obtained in the FCM clustering is shown below

Figure 4. Threshold Image

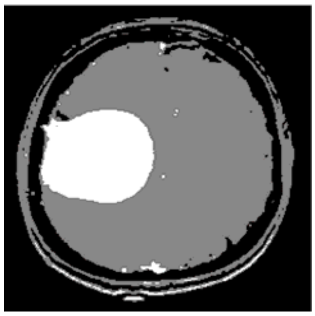


Figure 5. FCM Clustered Image

The Figure 6 is the set of clusters obtained from the FCM Clustering. In the set there are three clusters which are also called as the object. In the Figure 6 the 3rd cluster shows the tumor but, along with the tumor some noise is also present which needs to be filtered. After filtering the 3rd cluster alone, the resulted image is shown below. The size of the tumor portion by FCM Clustering is 6303 which is shown in the Figure7.

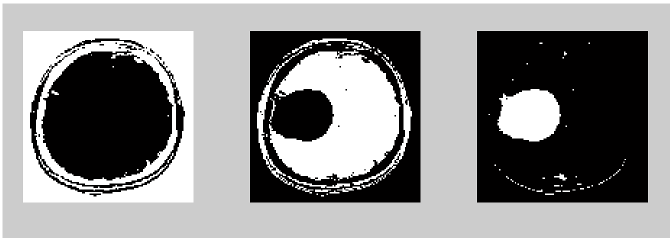


Figure 6. Clusters Obtained from FCM Clustering

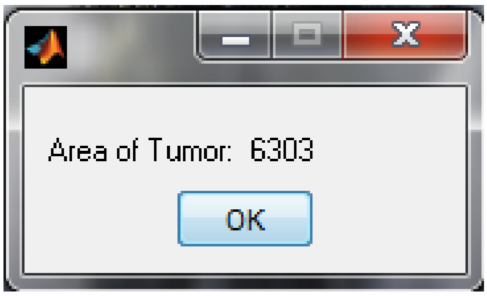


Figure 7. Size of Tumor Portion by FCM Clustering

In the Figure 8 there are four clusters and each cluster has different pixel value. The 4^{th} cluster shows the tumor part which is same as obtained from FCM clustering but it looks smaller than the tumor region obtained from FCM clustering. Also along with the tumor some additional noise is present that is filtered out to get the exact size of the tumor which is stated below. The size of the tumor obtained from K-Means is 6020 µm2 shown in Figure 9.

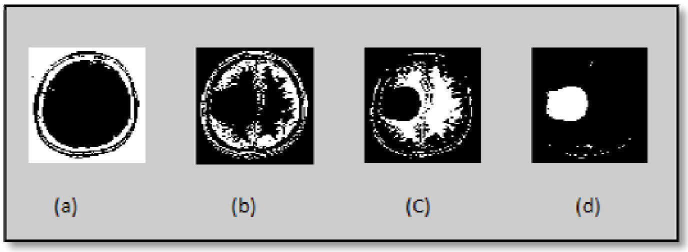


Figure 8. Clusters Obtained From K-Means Clustering

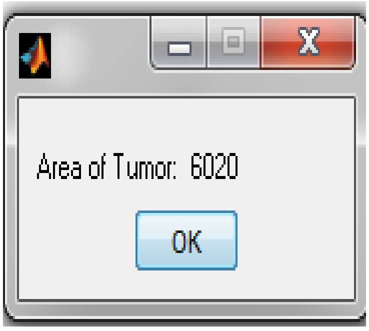
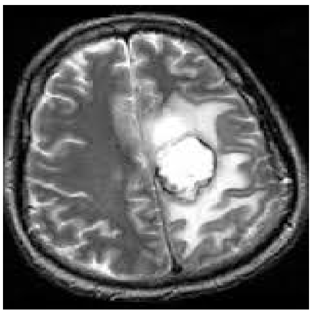


Figure 9. Size of Tumor Portion by K-Means Clustering

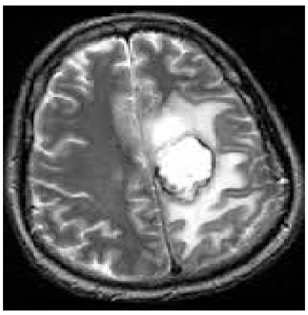
6.2 Results for Implementation of Bandelet Transform for Brain tumor detection

6. 2. 1. Outputs for Bandelet Transform using Arithmetic Entropy Encoding

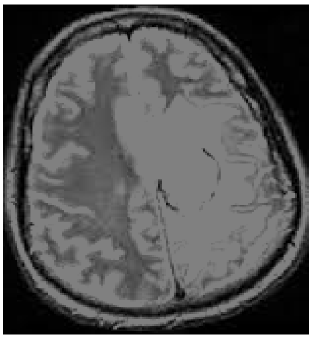
The brain images belonging to normal and abnormal category are subjected to bandelet transform whose coefficients are encoded for bit stream transmission from the source end. The encoded bits are then decoded and further subjected to Inverse Bandelet transform for obtaining the original image at the receiver end. The encoding and decoding is done using Arithmetic entropy encoding and Predictive entropy encoding. The results for compression using Arithmetic entropy encoding of the 4D fMRI images using the proposed compression scheme are shown in Figure 10 (a) to (j).



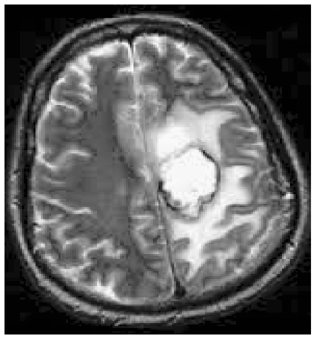
(a). Original Brain Image with Abnormality



(b). Forward Bandelet transformed Image with Abnormality

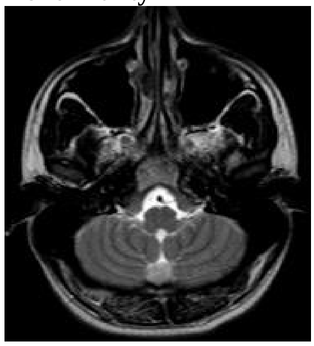


(c). Bandelet thresholding for brain image with Abnormality



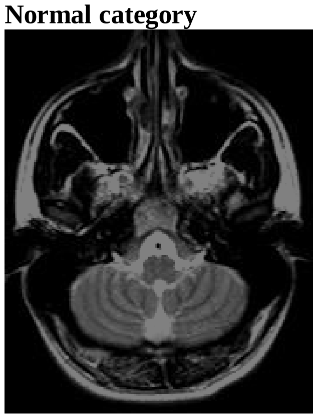
(d). Bandelet Fuzzy thresholding with Abnormality

(e). Compressed Image with Abnormality



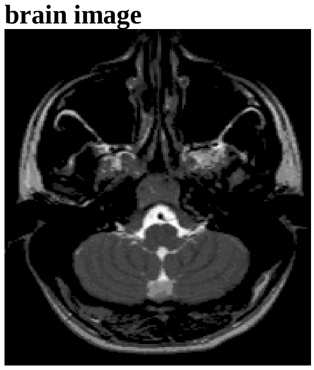
(f). Original Brain Image of Normal category

(g). Forward Bandelet transformed Image of normal category



(h). Bandelet thresholding for normal category of the brain image

(i). Bandelet Fuzzy thresholding for normal category of the brain image



(j). Compressed Brain Image of Normal category

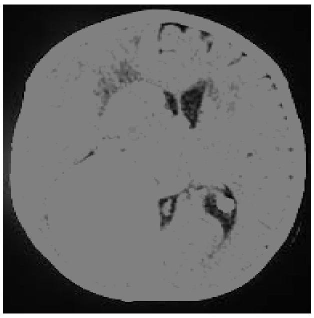
Figure 10. Results for Bandelet transform using Arithmetic Entropy Encoding

6. 2. 1. Outputs for Bandelet Transform using Predictive Entropy Encoding

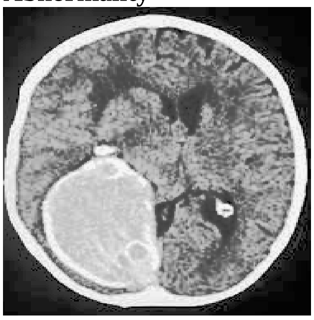
Similarly the Figure 11(a) to (j) depicts the results for bandelet transform using predictive entropy encoding. The Artificial Neural Network (ANN) has the capacity to predict the future outputs with the help of the present outputs, inputs and other related network parameters.

(a). Original Brain Image with Abnormality

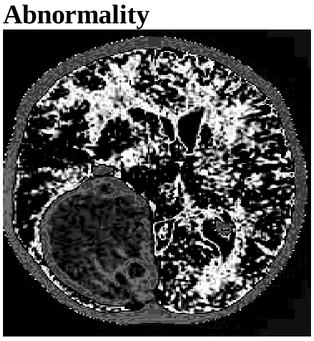
(b). Forward Bandelet transformed Image with Abnormality



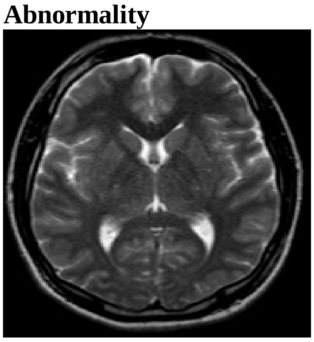
(c). Bandelet thresholding for brain image with Abnormality



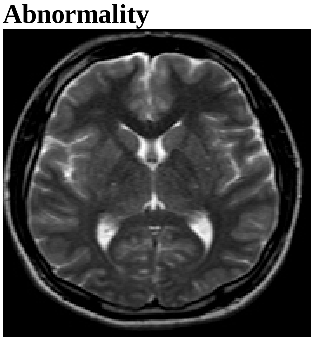
(d). Bandelet Fuzzy thresholding with Abnormality



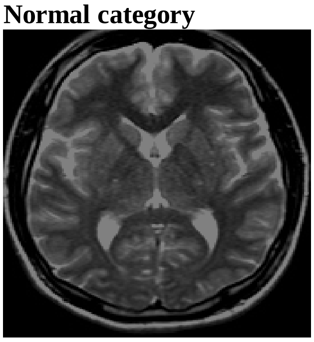
(e). Compressed Image with Abnormality



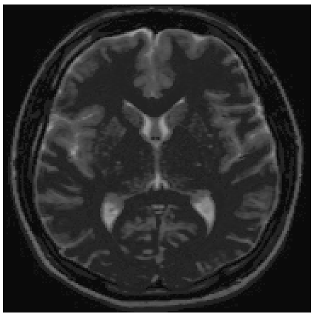
(f). Original Brain Image of Normal category



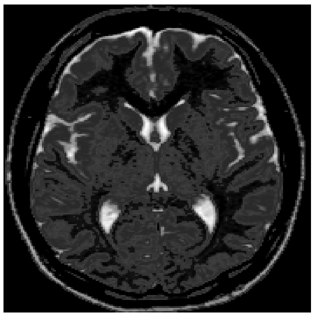
(g). Forward Bandelet transformed Image of normal category



(h). Bandelet thresholding for normal category of the brain image



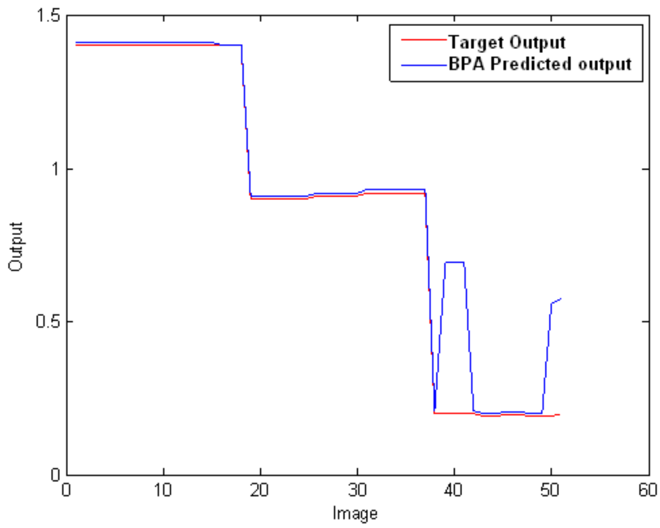
(i). Bandelet Fuzzy thresholding for normal category of the brain image



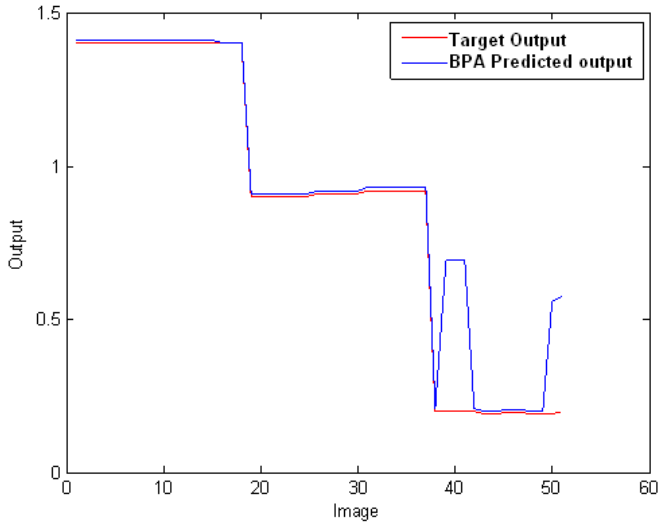
(j). Compressed Brain Image of Normal category

Figure 11. Results for Bandelet transform using Predictive Entropy Encoding

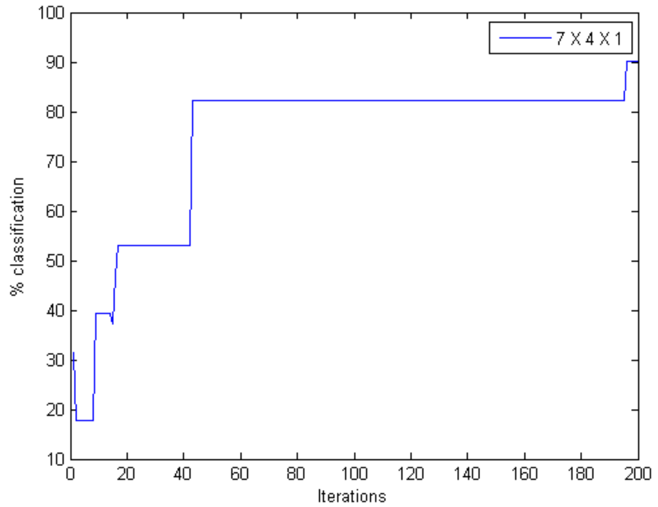
The Feed Forward (FF) ANN is trained using Back Propagation Algorithm (BPA) which serves as the first step in implementing predictive entropy encoding. Figure 11(a) to (c) illustrates the outputs for the encoder which uses FFANN trained with BPA. From Figure 11(a) it is evident for the abnormal brain images have a close match between target and predicted values (range 0. 9 to 1. 5) and for normal brain images the match between target and predicted values is in the range of 0. 3 to 0. 89. The network parameters for training the ANN is tabulated in Table 2.



(a). Target Vs Estimated output



(b). Iterations Vs MSE



(c). Classification Efficiency

Figure 11. Outputs for Bandelet transform with Predictive entropy encoding for compression

Table 2. ANN parameters for Predictive Entropy Encoding

S. No	Network parameters	Value
1.	No. of nodes in input layer	7
2.	No. of nodes in hidden layer	4
3.	No. of nodes in the output layer	1
4.	Activation function – hidden layer	Sigmoid
5.	Activation function – Output layer	Sigmoid
6.	Mean Squared Error	0. 0198
7.	No. of iterations	200
8.	Learning factor	0. 9

6.3 Performance Evaluation

The performance of the Bandelet transform using Arithmetic and Predictive entropy encoding are substantiated using Compression Ratio (CR) and the Mean Squared Error (MSE). These values are recorded in the Table 3 which states that bandelet transform with predictive entropy encoding is efficient.

Table 3. Performance Evaluation for Compression 4D fMRI Images using Bandelet transform

Size of Original/ Compressed Image (Normal Category) in bytes	Arithmetic Entropy Encoding	Predictive Entropy Encoding
58500 6900	MSE – 0. 355 CR – 0. 128	MSE – 0. 0198 CR – 0. 098
Size of Original/ Compressed Image (Abnormal Category) in bytes	**Arithmetic Entropy Encoding**	**Predictive Entropy Encoding**
7380 1810	MSE – 0. 245 CR-0. 114	MSE – 0. 0198 CR – 0. 069

7. Conclusion

This research work presents a compression scheme based on bandelet transform and fuzzy thresholding technique. The image is bandelet transformed to obtain bandelet coefficients and then apply fuzzy thresholding. Further arithmetic coding and predictive coding is used to compress the image. The above scheme has been applied to 4D fMRI brain images. It can also be applied to other medical images. The proposed scheme gives better results in terms of compression ratio. Further the work can enhanced using various other types of ANN algorithms for predictive encoding scheme.

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