# Wavelet based Independent Component Analysis for Multispectral Brain Tissue Classification

Sindhumol S., Anil Kumar, and Kannan Balakrishnan

***Abstract*—Multispectral analysis is a promising approach in tissue classification and abnormality detection from Magnetic Resonance (MR) images. But instability in accuracy and reproducibility of the classification results from conventional techniques keeps it far from clinical applications. Recent studies proposed Independent Component Analysis (ICA) as an effective method for source signals separation from multispectral MR data. However, it often fails to extract the local features like small abnormalities, especially from dependent real data. A multisignal wavelet analysis prior to ICA is proposed in this work to resolve these issues. Best de-correlated detail coefficients are combined with input images to give better classification results. Performance improvement of the proposed method over conventional ICA is effectively demonstrated by segmentation and classification using k-means clustering. Experimental results from synthetic and real data strongly confirm the positive effect of the new method with an improved Tanimoto index/Sensitivity values, 0.884/93.605, for reproduced small white matter lesions.**

***Index Terms*—Independent Component Analysis, Magnetic Resonance Imaging, Multispectral Analysis, Wavelet Transforms.**

## I. INTRODUCTION

MAGNETIC Resonance Imaging (MRI) for clinical purposes involves acquisition of multiple sequences like T1-weighted, T2-weighted, Proton Density (PD), Fluid Attenuated Inversion Recovery (FLAIR) etc. with each sequence providing a repository of unique information on different tissues [1]. For example, in brain imaging T1-Weighted Images (T1WI) show considerable contrast between Gray Matter (GM) and White Matter (WM), and T2-Weighted Images (T2WI) are good in imaging edema. FLAIR images suppress Cerebro Spinal Fluid (CSF) effects and give the details of hyper-intense lesions. MR multispectral suite constructed from the co-registered images of these sequences can help radiologists to do simultaneous analysis of abnormal tissues and affected locations [1].

A typical multispectral MRI classification system includes pre-processing, band selection, feature extraction/feature selection and classification as major steps. Feature extraction and selection is the most prioritized task [2] since classification accuracy is highly dependent on the selected feature sets. Transform based dimensionality reduction techniques like Principal Component Analysis [3], Independent Component Analysis (ICA) [3], [4] and their extensions [5]-[8] are widely used in feature extraction from multispectral MRI images. In a recent study, quantitative analysis of brain tissue classification using ICA [7] confirmed the efficiency of the method in clinical MRI applications. However, these global transforms often fails to keep the local characteristics in classification results. Dependency of the input multispectral data sometimes badly affects the accuracy of unmixed components. Multiresolution analysis using wavelet transforms [9] and its new extension, curvelet transform [10], have proved its potential in medical image segmentation with accurate clinical results [11]. Curvelets are found to give superior performance in local geometric feature analysis, but wavelets still keep its position in 1-D signal analysis [10], [11]. So, multisignal wavelet decomposition is adopted in this work to analyze the spectral signatures corresponding to each pixel in the multispectral cube. Wavelet based ICA extensions resolving similar issues in several domains [12]-[15] gave the background to continue with this new technique for simultaneous MRI sequence analysis.

Multisignal wavelet analysis in the spectral domain is proposed in this work to preserve the global and local information with equal priority in ICA for multispectral MRI analysis. A correlation based feature selection method is also included to select the level of wavelet decomposition for subband analysis. The best uncorrelated detail coefficients are selected from a level providing minimum degree of correlation [15] among the subcomponents, and combined with input images in ICA computation. To measure the improvement in classification by the extracted features from the proposed method, a preliminary evaluation of the reproduced tissues is conducted with a simple unsupervised classification method, k-means clustering [3]. Performance of the algorithm is analyzed and confirmed by a comparative study using ICA

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based classification for synthetic and clinical data. Observed results from visual and quantitative analysis support new algorithm as a promising method in projecting both local and global features in clinical analysis.

This paper is organized in the following manner. Section II briefly explains the proposed method and techniques involved in it. Details of the experimental datasets, results and discussions are summarized in Section III. Section IV concludes the paper.

## II. PROPOSED METHOD

Wavelet decomposition of the spectra and ICA are the core concepts used in this work. Major steps involved in this method are depicted in Fig. 1. Co-registered corresponding images from different MRI sequences were collected to form a multispectral suite. Each pixel vector represents the spectral signature of the area specified by that pixel. The proposed algorithm can be summarized as follows:

*Step1*: Consider input multispectral image as a collection of spectral signatures. Apply 1-D multisignal wavelet decomposition on these signals to divide the spectral domain into low frequency and high frequency components.

*Step2*: Calculate correlation coefficient '$\rho$' between the high frequency subcomponents for each level using the eq.,

$$\rho\left(D_1, D_2\right) = \frac{\operatorname{cov}(D_1, D_2)}{\sigma_{D_1} \cdot \sigma_{D_2}} \qquad (1)$$

where 'cov( $D_1$, $D_2$ )' is the covariance between datasets '$D_1$' and '$D_2$'. $\sigma_{D_1}$ and $\sigma_{D_2}$ are the standard deviations of '$D_1$' and '$D_2$' respectively. Select the detail coefficients providing minimum degree of correlation for further analysis.

*Step3*: Combine the output from *Step2* with input multisignals and apply FASTICA [4] algorithm on newly formed dataset.

*Step4*: Apply unsupervised classification method K-means clustering on extracted components from *Step3* and observe the classified brain matters.

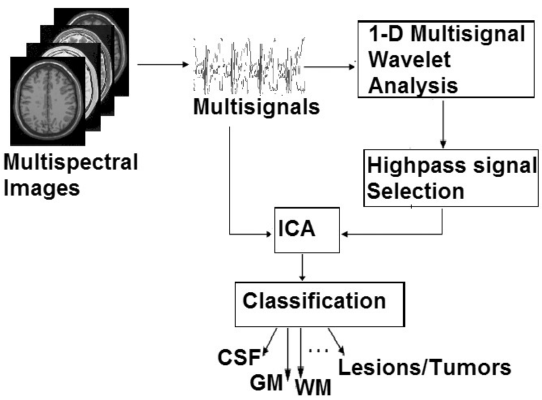



Fig.1. Proposed Method

### A. Wavelet Decomposition and Feature Selection

Discrete wavelet transform is applied on input image cube in the spectral domain as shown in Fig. 2, exploiting the same concept used in the spatial domain [15]. A Low Pass Filter (LPF) and its corresponding High Pass Filter (HPF) are simultaneously applied on input multispectral data at each level 'i'. It decomposes the spectra into detail coefficient Di and approximation coefficient Ai as shown in Fig. 2. Extra elements involved in the signals are eliminated by a dyadic decimation, which halves the original resolution. Recursive application of this procedure on approximation coefficients generates increasingly smoother versions of the original signals. In practice, the high frequency subcomponents are independent and low frequency components are weakly dependent [15]. This property is used in this work to preserve the local characteristics, and to improve the feature extraction.

The problem with wavelet decomposition is to decide the level of decomposition [15] for selection of best subband coefficients to do ICA. A simple method using the correlation coefficient between detailed coefficients at each level calculated by eq. (1) helps to do this. The magnitude of the computed correlation coefficient shows the degree of similarity between the subcomponent images.

### B. Independent Component Analysis

It is a widely used spectral unmixing technique in multispectral data analysis. Mathematically it finds a linear representation of non-gaussian data so that the components are statistically independent, or as independent as possible [4]. Let **x** be a column vector $\mathbf{x}=[x_1, x_2...x_n]^T$, where $x_i$'s are mixtures, and $\mathbf{s}=[s_1,s_2...s_m]^T$ be the sources. Using the vector-matrix notation, the above mixing model can be written as [4].

$$\mathbf{x}=\mathbf{A}\mathbf{s} \qquad (2)$$

where '**A**' be the matrix with elements $a_{ij}$ . '**A**' can be estimated and its inverse '**W**' can be obtained to calculate the independent components by using eq.

$$\mathbf{s}=\mathbf{W}\mathbf{x} \qquad (3)$$

In this work MR image cube is considered as a collection of 'P' dimensional unmixed pixel vectors. FastICA [4] method is applied to extract the 'm' brain matter classes $s_1, s_2, \ldots, s_m$, by means of a 'P x m' mixing matrix '**A**' using eq. (3).

## III. EXPERIMENTAL RESULTS

Both synthetic and clinical images were considered to evaluate the performance improvement of the proposed method. As a comparative study, feature extraction using ICA was also conducted in the same environment. All these

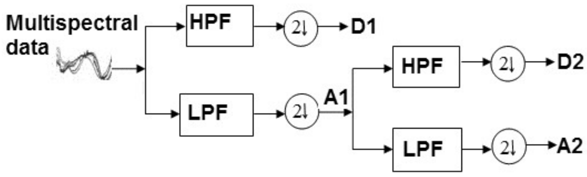
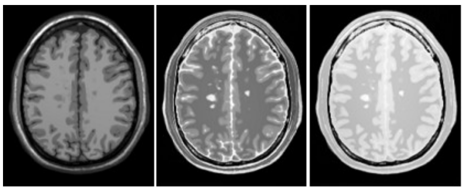



Fig. 2.Wavelet Analysis of multispectral data

experiments were done with Matlab 7 implementation in Windows 7. Multisignal 1-D wavelet decomposition functionality available from Wavelet Toolbox was used in spectral analysis with the help of Daubechies 2 (db2) wavelet. K-means clustering provided in Statistical Toolbox classified the tissues from extracted Independent Components (ICs) with parameter settings, number of clusters = 4 and Distance measure= 'city'.

### *A. Synthetic Image Analysis*

The synthetic MR image analysis included a set containing Multiple Sclerosis (MS) data, obtained from the BrainWeb Simulated Brain Database at the McConnell Brain Imaging Centre of the Montreal Neurological Institute (MNI), McGill University. 10 multispectral datasets containing axial T1WI, T2WI, and Proton Density Images (PDI) were considered for analysis. Slices from each sequence were selected with parameter settings 1-mm slice thickness and noise level of 0%. T1WI, showing WM and GM components, T2WI showing CSF matters and White Matter Lesions (WML), PD images showing more abnormal mattes are given in Fig. 3(a). Selected ICs from proposed method are summarized in Fig. 3(b) and ICs from conventional ICA are shown in Fig. 3(c). A more specific, component-wise tissue categorization compared to ICA results is available from the proposed method, and it locates the abnormality information in a separate IC. It can be observed from Fig. 3(c) that ICA results fails to distinguish the small white matter lesions efficiently.



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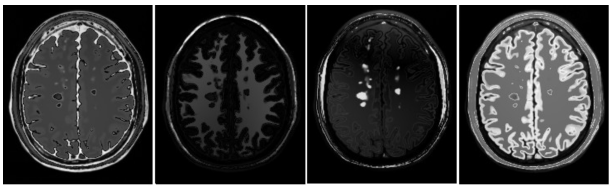

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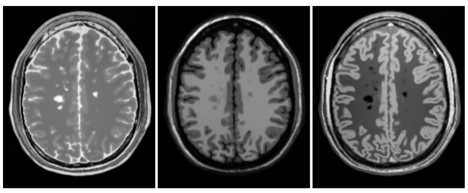


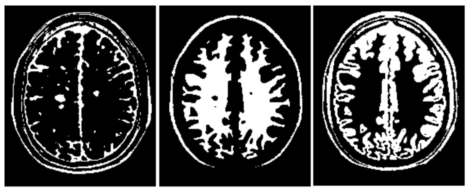
(c)

Fig. 3. Synthetic input images and unmixed components. (a) synthetic images T1WI, T2WI and PDI , (b) independent components from proposed method, (c) independent components from ICA.

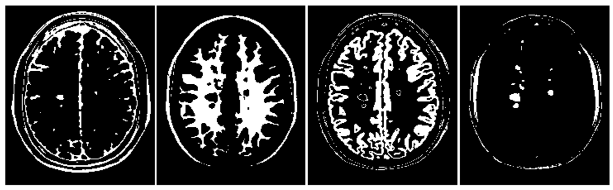
Results from classification using ICA and proposed method are shown in Fig. 4(a) and Fig. 4(b) respectively. From Fig. 4(a) it can be seen that conventional ICA cannot distinguish WML and CSF without assistance from radiology experts, whereas proposed method clusters the CSF and WML into different classes as shown in Fig. 4(b). Visual analysis confirms the efficiency of the proposed method in local feature specifications by exactly locating the presence of abnormality in WM as shown in Fig. 4(b). Irrelevant tissues visible in the classified results were removed with the help of an experienced radiologist, and a quantitative analysis was conducted using groundtruth images. Average Tanimoto index [7], sensitivity, accuracy and False Positive Rate (FPR) values measured for 10 multispectral samples are summarized in Table I. Improved Tanimoto indices for all brain tissues and WML confirm the efficiency of the proposed method in classification over ICA based methods. False pixels rate is also found to be very less for proposed method compared to ICA based results.

TABLE I
QUANTITATIVE ANALYSIS OF BRAIN TISSUES

| Brain Matter | Feature Extraction | Tanimoto Index | Sensitivity | Accuracy | False Positive Rate |
|---|---|---|---|---|---|
| CSF | ICA | 0.7412 | 75.653 | 98.045 | 0.165 |
| | Proposed Method | 0.7130 | 81.177 | 98.506 | 0.661 |
| GM | ICA | 0.6976 | 88.919 | 94.608 | 4.467 |
| | Proposed Method | 0.8035 | 89.701 | 96.929 | 1.894 |
| WM | ICA | 0.8782 | 99.987 | 97.194 | 3.514 |
| | Proposed Method | 0 .9143 | 98.951 | 97.907 | 2.397 |
| WML | ICA | 0.6352 | 71.826 | 99.569 | 0.202 |
| | Proposed Method | 0.8839 | 93.605 | 99.901 | 0.072 |



(a)



(b)

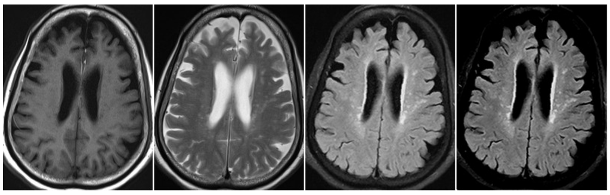
Fig. 4. Classification results. (a) from ICA, (b) from proposed method.

### B. Clinical data Analysis

The second experiment was conducted using clinical datasets as shown in Fig. 5(a). Abnormal images of T1WI, T2WI and FLAIR sequences were considered. Two FLAIR sequences with different parameters were involved to form a multispectral data with four bands. All of these images were sampled by Siemens' whole body 3 Tesla (T) MR system (Siemens, AG Medical Solutions, Erlangen, Germany). MATLAB based registration was performed on these dataset to generate co-registered images. T1WI shows WM, T2WI projects fluid and abnormal points, FLAIR images gives information on abnormal tissues. No direct information on GM is available from these images. The proposed method and ICA was repeated in the same environment of synthetic data analysis. Classification results from ICA and proposed method are shown in Fig. 5(b) and Fig. 5(c) respectively (in the order of CSF, GM, WM and Abnormality from left to right).

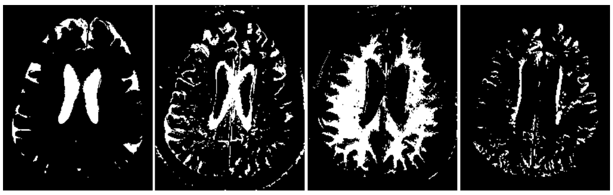
It is observed from Fig. 5(b) and Fig. 5(c) that proposed feature analysis algorithm could give more specific results compared to ICA based classification. Last column results demonstrate that the abnormal tissues classified from proposed method is very similar to those observed from FLAIR images. Abnormality presence in WM (3rd column) is also well located by proposed method.

Visual and quantitative analysis results from proposed method, and their comparison to conventional ICA based classification results support the new method as a superior feature extraction method for improved MRI tissue classification, especially for analysis of small lesions as shown in visual classifications.



(a)

(b)



(c )

Fig. 5. Clinical input images and classification results. (a) T1WI, T2WI, FLAIR1, FLAIR2, (b) Classification results from conventional ICA, (c) Classification results from proposed method

## IV. Conclusion

A new multisignal wavelet analysis based ICA algorithm is proposed in this work for multispectral brain tissue analysis from MRI sequences. Comparative study with conventional ICA results confirmed the positive impact of the new method in local feature analysis. From preliminary results from visual and quantitative analysis using k-means clustering, it is observed that proposed method is a promising approach in small abnormality detection and brain tissue analysis. A detailed analysis of the new algorithm using supervised classification techniques like SVM is under consideration as a future work.

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