

A NEW METHOD FOR COLOURIZING OF MULTICHANNEL MR IMAGES BASED ON REAL COLOUR OF HUMAN BRAIN

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ABSTRACT

In this paper, we propose a novel approach for colourizing of multichannel MR images based on real colour of human brain. At first, we use independent component analysis (ICA) to transfer three MR modalities into different representations, which enhance the physical characteristics of tissues. Then, Statistical Features are extracted from three independent components and their wavelet coefficients to generate a feature vector for each pixel of images. Huge amount of features are reduced by using some feature reduction methods such as Principle Component Analysis (PCA) to classify the brain into 3 primary classes. The colour space of Visible Human Project (VHP) dataset is quantized to 10 colours by using a partially supervised algorithm included self-organization map and Linear Vector Quantization (LVQ) algorithms. Acquired 10 colours are allotted to each pixel based on texture and intensity of image in two different steps. Consequently, a fast-automated algorithm is proposed, which has low sensitivity to variation of pixel intensity and precise result regarding to VHP images.

1. INTRODUCTION

Medical images from different modalities can provide complementary information about anatomy or physiology in a synergistic manner. T1-weighted, T2-weighted and proton-density-weighted (PD), which is obtained from MRI systems, are popular modalities in practical medical diagnosis and these are widely used in image processing. Although these images show the anatomical structure of the patient with an accuracy of millimetres, the intensity value in the images only represents the time constant of spin relaxation in the case of MRI. The intensity value does not represent the colour. In recent years, there has been considerable research effort to the colouring of medical images. However, these methods cannot represent a realistic colour due to employment of linear mapping to transfer the colour to tissues. In 2001, Muraki et.al introduced an elementary non-linear mapping method using Radial Basis Function (RBF) network [1]. They used ICA to extract independent components of MR modalities. However, that method is based on intensity colour mapping that make it sensitive to noise and image artefact as well as needing a long time to perform a colour result.

In this paper, we present a new approach, which has a fast and reliable performance and fine colour in comparison with

Visible Human Data (VHF), distributed by national Library of Medicine (NLM). ICA is applied to three modalities to separate the components of interest, which are due to task-related brain activation, from other components [2]. Some robust statistical features are extracted from three independent images and their wavelet coefficients, which contain textural and spatial information about images. Best features are selected using some feature reduction methods such as PCA and used for segmenting brain into some classes and eventually these classes are mapped into colour space regarding a new colour space quantization algorithm based on Linear Vector Quantization (LVQ). This algorithm has completely described in separate article [3].

The remainder of the paper is laid out thus: Section 2 discusses the Independent Component Analysis (ICA) which obtains independent images. Next, Section 3 describes features, which are used in texture description and image segmentation. Segmentation and classification of images using fuzzy c-means (FCM) and etc. will be described in Section 4. In Section 5 colour quantization of brain images applying a new method is detailed. Eventually, proposed method and experimental results of this paper is discussed, followed by some conclusions in Section 5 and 6.

2. INDEPENDENT COMPONENT ANALYSIS (ICA)

In magnetic resonance images (MRI) observed data is a superposition of some underlying unknown sources such as White matter, Gray matter, cerebro-spinal fluid (CSF) and etc. In addition, three utilized modalities, which are used in this approach, are highly correlated with each other and correspond to mixture of physically independent components. Therefore, we need to obtain three independent images, each of them represent one of reminded tissues. This separation of independent sources is reachable by using of ICA.

Three modalities of T1-weighted, T2-weighted and proton-density-weighted (PD) from Visible Human Data (VHD) has been selected as an observed vector $X = [X_1, X_2, X_3]^T$ and ICA exerted to achieve three independent sources $S = [S_1, S_2, S_3]^T$, as

$$X = A \cdot S \quad (1)$$

ICA is considered to be the problem of finding a matrix A and the data sets S that make each element of S as independent as possible. In practice, finding A and S simultaneously

from X is impossible. Usually, we start from an appropriate matrix W to define

$$Y = W \cdot X \quad (2)$$

and modify W iteratively so that each element of Y becomes as independent as possible. If the iteration converges, Y is considered equivalent to S apart from the scale and the permutation [1].

For this purpose, the X vector has been centred and whitened using PCA, at first. Then, using the FastICA algorithm, matrix W has been computed. Once vector W has become available, an ICA vector S can be computed from

$$S = W^T \cdot X \quad (3)$$

Therefore, we can separate physically independent tissue components from the multichannel MRI data by using ICA. These components are suitable for determining the correspondence with the tissue colour.

3. FEATURE EXTRACTION APPROACH

The feature extraction in a MR images is of interest because might contain essential information. The detection of these features is an important step in segmenting an image for colouring purposes. When multispectral images are used, the result of ICA on intensity vectors or MR tissue parameters T1, T2 and PD can be used as input features. The reason of using ICA of image modalities as an input feature is that, it carries information rendered by all MR characteristics of the tissue class. Although we use independent component of signal intensities at the pixel sites as input features to the segmentation process, it can be easily extended when other features such as statistical and spatial features of the intensities are. In this paper, the following three feature sets have been used:

- 1-First-order statistical features obtaining from ICA approach.
- 2-Wavelet packet based feature containing spatial and highly textured information
- 3-Combination of statistical features and wavelet packet based features.

3.1. First order statistics

Smooth regions can be segmented using local grey level statistics such as mean, variance, maximum, minimum, energy, skewness, kurtosis and etc. in a neighborhood of each pixel. First-order statistics are one of the most significant statistical features which are quite straightforward. They are computed from a function that measures the probability of a certain pixel occurring in an image. This function which is also known as histogram is defined as follows:

$$H(g) = \frac{n_g}{N}; g = 0, 1, \dots, G-1 \quad (4)$$

where N is the number of all pixels in an image, G is the number of gray levels and n_g is the number of pixels of value g in an image. The following measures could be extracted by using first-order probability distribution.

Mean:

$$P_1 = \sum_{g=0}^{G-1} gH(g) \quad (5)$$

Variance:

$$P_2 = \sum_{g=0}^{G-1} (g - P_1)^2 H(g) \quad (6)$$

Skewness:

$$P_3 = \frac{\sum_{g=0}^{G-1} (g - P_1)^3 H(g)}{P_2^3} \quad (7)$$

Kurtosis:

$$P_4 = \frac{\sum_{g=0}^{G-1} (g - P_1)^4 H(g)}{P_2^4} \quad (8)$$

Entropy:

$$P_5 = -\sum H(g) \cdot \log(H(g)) \quad (9)$$

Energy:

$$P_6 = \sum_{g=0}^{G-1} H^2(g) \quad (10)$$

In addition to mentioned features which include coarse information about texture, spatial frequency-based features can be used for highly textured regions. The main reason we employ wavelet decomposition as a feature set is that, the textured region has more high-frequency component and the smoothing region has more low-frequency components. It has been demonstrated that the smoothed images in the high frequency embody the textural information of the image, where horizontal, vertical and diagonal sub-images comprise of the directional information of texture. For extracting textural information, we used wavelet packet, which has been described below.

3.2. Wavelet Packet

Wavelet transform could be explained as that the original signal is filtered by a series of band-pass filters in different scales. Therefore, we can decompose the signal to a series of frequency bands for analyzing and processing. DWT decomposes a signal in a set of channels whose bandwidth is smaller in the low frequency regions. This turns out to be sufficient for regular images whose information is concentrated at low frequencies, but not for textures. In the case of the DWT, only the low frequency block is redecomposed.

To avoid this drawback, we can use wavelet packet transform. Wavelet packet transform is a generalization of discrete wavelet transform that leads to over-complete set of basis functions. Wavelet packets have been described by the following collection of basis functions [4]:

$$\begin{aligned} W_{2^n} (2^{j-1} x - k) &= \sqrt{2^{1-j}} \sum_m h_0(m - 2k) \sqrt{2^j} W_n(2^j x - m) \\ W_{2^{n+1}} (2^{j-1} x - k) &= \sqrt{2^{1-j}} \sum_m h_1(m - 2k) \sqrt{2^j} W_n(2^j x - m) \end{aligned} \quad (11)$$

where j is a scale index, k is a translation index, h_0 is a low-pass filter, h_1 is a high-pass filter. The function w_0 can be identified with the scaling function f and W_l with the mother wavelet y . For discrete signal, wavelet packet coefficients may be computed efficiently as follows:

$$\begin{aligned}
 C_{2n,k}^{j-1} &= \sum_m h_0(m-2k).C_{n,m}^j \\
 C_{2n+1,k}^{j-1} &= \sum_m h_1(m-2k).C_{n,m}^j
 \end{aligned}
 \tag{12}$$

We have applied wavelet packets (coeflet8) to independent images for 2 levels and extracted some statistical parameters such as mean, energy, variance, skewness and kurtosis of each pixel in a specified neighborhood window, in some sub-bands of second level which comprises directional information of texture.

4. UNSUPERVISED SEGMENTATION

Unsupervised techniques, which are usually called clustering, automatically find the structure in the images. A cluster is an area in feature space with a high density. Some clustering methods include fuzzy c-means, Kohonen self-organizing map and Hopfield neural network.

The fuzzy c-means algorithm generalizes the K-means algorithm [5] allowing for soft segmentations based on fuzzy set theory. Unlabeled data are labeled by minimizing a generalized within group sum of squared error objective function.

Kohonen's self-organizing map generates nodes on a two-dimensional lattice in which the distribution of these nodes corresponds to the proximity of their associated node patterns in the feature space [6,7,8,9].

The Competitive Hopfield neural network (CHNN) is an artificial neural network that has been used in [10] for the classification of MR images via energy minimization. The energy function for minimization is defined as the mean of the squared distance measures of the gray levels within each class.

5. COLOUR QUANTIZATION

Colour quantization is preliminary and necessary process of colourizing images. It is practically impossible to generate a colour map with too many colours. In reducing colours, those more probable and more valuable should survive and others be omitted. These two properties do not occur simultaneously for all colours.

In brain images, there are rare colours representing important anatomic tissues. In this case, unsupervised clustering

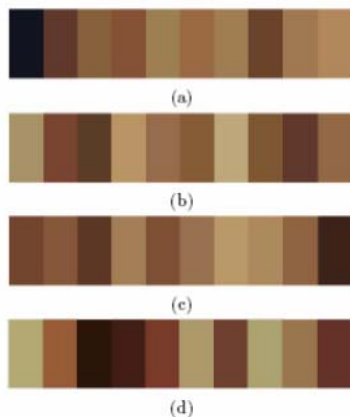


Figure 1 - Obtained colour map by using some different method: (a).Kohonen SOM, (b).FS-SOM, (c).FCM and (d). Proposed method

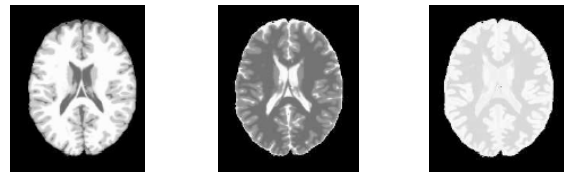


Figure 2 - Three stimulated MR modalities contained T1-weighted, T2-weighted and proton density

cannot reach into satisfying results. Rare but valuable colours can easily be omitted during fuzzy clustering, K-means, neural gas and similar approach. We have proposed to use semi-supervised vector quantization for colour reduction in brain images. In our study, quantization has been performed on occasionally labelled colour vectors. The labelled vectors include those rare colours which quantization should preserve them and produce prototypes for them. Our quantization strategy completely differs from independent LVQ and self-organization map (SOM). Interaction between two groups of colour samples enhances colour quantization quality. Our experimental examples of brain reduced colour images are so satisfying [3].

Hence, 10 brain-quantized colours have been employed here for colour map instruction. Further these 10 colours, a bilinear interpolation of them is also included in final colour map to prevent from discontinuity in quantized images. For such interpolation, colour arrangement is important; so the visually arranged version of 10 colours has been employed here. The colour map for brain images using semi-supervised algorithm is depicted in figure 1.(d). It's clear that rare colour is presented in this colour map but discarded in other methods.

6. PROPESED METHOD

In the current research, two different databases are used to compare the result on different images. The first one is simulated MR images from BrainWeb institution which contains simulated brain MRI data based on normal anatomical models, includes T1-weighted, T2-weighted and proton density modalities and the label of each pixel. Figure 2 shows a sample slice of these database modalities. As we know the label of each pixel so utilize of simulated images make the task of validating a segmentation method easy. MR images from Harvard Medical School, is another dataset to examine the result of proposed method on in vivo images. Figure 3 depicts three modalities of the database.

Figure 5 depicts block diagram of proposed method to colour MR images. At first step, we used FastICA to perform ICA on the mentioned datasets and obtained three independent components, which enhance the physical characteristics of tissues. Feature extraction process has been used to obtain best feature set to segment the images, as

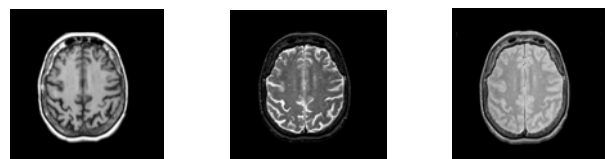


Figure 3 - Three modalities from Harvard medical school database

Table 1. Percentage of correctly classified pixel to three general tissues based on different feature sets

Seg. method \ Tissue	First-order Statistic(stat.)	WaveletPacket (wavelet)	Combination of stat. and wavelet
Gray matter	95.2	88.6	91.2
White matter	74.3	75.1	92.7
CSF	76.9	85.4	96.5

it has been described previously. The main idea of using reminded features is to classify pixels based on their statistical and spatial information rather than their intensities only. We constructed three sets of features: statistical features with 3*8 dimensions for three images, wavelet packet based features with 3*10 dimensions and combination of statistical and wavelet packet based features with 3*18 dimensions. Therefore, we need a system to select the best set of features regarding to the result of segmentation of these feature space. We avoid the effect of segmenting algorithm in selecting the best feature space, whereas we have used three vigorous algorithms, employed formerly. These algorithms included of fuzzy c-mean, kohonen self organization map and Hopfield neural network.

In order to reduce computational complexity and improve the classification performance those features that may be irrelevant or redundant have been discarded by Fisher's linear discriminant analysis (LDA). LDA finds that feature space which maximizes the ratio of between-class to within-class variation jointly for each feature (dimension). PCA could be further applied to find a compact subspace to reduce the feature dimensionality. After employing feature selection and reduction methods, we have had five features for statistical feature set, eight features for wavelet based feature set and eight features for combination of these two feature sets. The result of applying these feature sets to segment the images into three general classes (white matter, gray matter and CSF.) has been shown in table 1.

Three different segmentation methods subsequently have been applied to the best features obtained previously. Segmentation results for each dataset have been compared to the specified labels in simulated images and the average number of pixels that classified correctly has been calculated. Table 2 depicts the percentage of these correct classifications for each algorithm. In fact, in current research, we have not focused

Table 2. Result of different method of segmentation on different feature set

Feature set \ Seg. method	First-order Statistic(stat.)	Wavelet Packet (wavelet)	Combination of stat. and wavelet
Fuzzy c-means	82.6	93.3	97.6
SOM	78.5	81.4	91.1
Hopfield	75.3	84.6	89.4

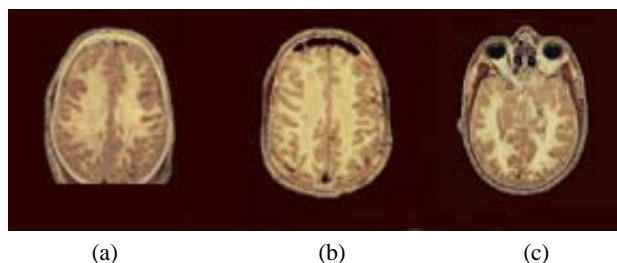
Table 3. Percentage of correctly classified pixel to three general tissues based on third feature set

Tissue \ Seg. method	Gray matter	White matter	CSF
Fuzzy c-means	95.2	88.6	91.2
SOM	74.3	75.1	88.7
Hopfield	76.9	85.4	90.5

on segmentation approach, so we have selected some usual unsupervised segmentation methods and have used the best parameters, obtained in previous works. To read more details about these algorithms see [11,12,13,14].

Achieved result has shown that fuzzy c-mean algorithm has the best performance to segment the image, when third feature set (combination of statistical and wavelet based features) is used. The percentage of correctly classified pixels of simulated MR images from brainweb dataset to three general tissues has been indicated in table 3. Result shows that all the tissues especially CSF has been classified better than other methods [15]. Above processes has been performed on real MR images and similar result has been shown for this dataset. Lower values in comparison with simulated MR images consequences are probable, due to available noises and parameter in MRI systems.

According to quantization of colour space to 10 major colours, we can specify the colours regarding to each three significant tissues, experimentally. For instance, orange or livid colour can just be appeared in Gray matter. This issue has been accomplished by an expert in MRI field and looking to all the images in Visual Human Female (VHF)¹ atlas. Consequently, we have had limited colours in each tissue which do not appear in other tissues. In regard to result of segmentation, each pixel has been appeared in one of the three classes and also we have known the colours of each tissue. Therefore, a simple mapping method can assign existing colours to specified pixel in that tissue. This mapping has been constructed by comparing the intensity of each pixel of class with the intensities corresponding to each colour. Figure 4

**Figure 4** - (a): Colour image from visible human project (VHP) atlas. (b), (c): Result of colouring simulated MR images using this method on two different slices.¹ Available in www.nlm.nih.gov.

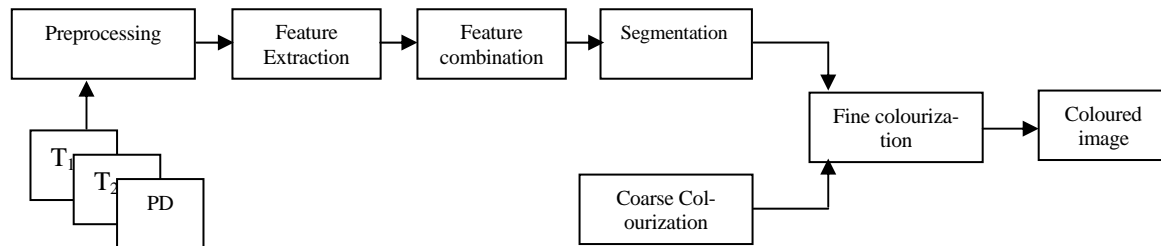


Figure 5. Block diagram of proposed method

depicts the result of colouring real MR images using this method.

Results prove that this method has more realistic colour comparing with previous methods and rare colour presented in result. In addition this method is more robust to noise than other methods, because we have used both textural and intensity information of image instead of only intensity information. This fact helps us to have a powerful method against usual parameters of MRI system such as intensity inhomogeneity and peripheral noises.

7. CONCLUSION

In this paper a new method for colouring brain MR images is proposed based on two scale processes. Initially, the input image is segmented into three major classes. Selecting of these major classes is performed by clustering on spatial and statistical features of independent image. Indeed each image pixels is classified to one of these three classes regarding to its textural information. There is a subset of quantized colours associated with each major class. The texture segmentation idea rises from the anatomical fact that presence of colours in each class of texture is restricted. Hence, a physician determines the divisions of colour space for each major class. The low scale segmentation determines a colour set for each pixel (regarding to its textural class) and does not determine exact colour. The final step is fine colour selection using intensity colour map, against previous processes that deal with texture.

The final step is the process on individual pixel intensity and enhances final colour image quality by introducing high frequency details. Although intensity colour map is completely unusual, but in this study three maps are predefined. Therefore, that pixel class picks one of them. Consequently, employed colour map is constrained by texture which increase certainly for medical colouring.

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