Automatic Tumor Segmentation of Brain in MRI

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Abstract

In this paper, we present a new method to classify tumor in multispectral magnetic resonance (MR) images of the human brain. The MRI's consist of three magnetic resonance parameters proton density, T1-weighted, and T2-weighted images, which are processed with multispectral analysis. The proposed approach, called Constrained Energy Minimization (CEM) was developed in [12] where only the knowledge of the desired signature to be classified was required. It was derived based on the Minimum Variance Distortionless Response (MVDR) in array processing. CEM considers an MR image classification problem as an array-processing problem where each sensor represents one spectral band. It uses a finite impulse response (FIR) filter to minimize the output power while the desired signature is constrained to a specific gain. The method has been evaluated through several experiments. Results show that the cerebral tissue was segmented accurately into four images, tumor, gray matter, white matter and cerebral spinal fluid indicating the possible usefulness of this method. As far as computing saving is concerned, the experimental results also show computational complexity improvement.

Key word – Constrained Energy Minimization (CEM), Magnetic resonance imaging, Classification, Brain images, Tumor.

1. Introduction

Magnetic Resonance Imaging (MRI) has become recognized as a useful method since it provides unparalleled capability of revealing soft tissue contrast as well as 3-D visualization. It has widely used in the research study and clinical diagnosis of brain and body. In clinical diagnosis, MRI can provide multispectral images of free water, proteinaceous fluid, soft tissue and hard tissue with a variety of contrast using three parameters T1-weighted, T2-weighted and dual echo-echo proton density (PD) images. With multispectral abundance signatures, it is more useful for a clinician in clinical practice over other techniques.

Brain parenchyma classification and segmentation of normal and pathological tissue is the first step in addressing a wide range of clinical problem. Via analysis of the volume, shapes and region distribution of the brain tissue, one can identify the abnormalities that are commonly related to the conditions of heterotopia, lissencephaly, brain atrophy, and cerebral infarction. Over the past years many computer-assisted methods have been reported [1]-[4]. Among them, neural networks have demonstrated superior performance in the segmentation of brain tissue over classical maximum likelihood methods [5]-[9]. Hybrid methods based on both imaging processing and model-based techniques seem promising for segmentation by selecting the image processing parameters automatically [10]. Knowledge-based techniques have also been explored to make more intelligent classification and segmentation decisions. [11].

In this paper, we demonstrate a Constrained Energy Minimization (CEM) technique, which has shown great potential promise in hyperspectral image classification and target detection [12]. Its applicability applied to the MR image has not been investigated. The idea of CEM is to consider the MR image classification problem as an array-processing problem where each sensor represents one spectral band. It designs a Finite Impulse Response (FIR) filter, which pass the desired target with a specific gain so that the filter output resulting from unknown source can be minimized. Through the CEM processing, the data dimensionality of MRI can be decreased and the desired signature of interest can be enhanced. In order to evaluate the effectiveness of CEM, a series of experiments are conducted using brain MR images. The experimental results show that the proposed CEM technique can automatically segment tumor, gray matter, white matter and cerebral spinal fluid accurately.

The remainder of this paper is organized as follows. Section II describes the constrained energy minimization approach. Section III conducts a set of experiments to evaluate the effectiveness of CEM in classification performance when MR images are used for analysis. Section IV concludes with some comments on the results achieved.

2. The Constrained Energy Minimization (CEM) Approach

A recent approach, called Constrained Energy Minimization (CEM) [12] was developed for the target detection and classification in which the only required knowledge is the target signature. CEM used a finite impulse response (FIR) filter to constrain the desired signature by a specific gain while minimizing the filter output power. The main idea of CEM is based on Minimum Variance Distortionless Response (MVDR) in array processing [13]-[15] with the desired signature interpreted as the direction of arrival from a desired signal. The method can be derived as follows.

Assume that we are given a finite set of observations $S = \{\mathbf{r}_1, \mathbf{r}_2 \ldots \mathbf{r}_N\}$ where $r_i = (r_{i1}, r_{i2} \ldots r_{iL})^T$ for $1 \le i \le N$ is a sample pixel vector. Suppose that the desired signature **d** is also known a priori. The objective of CEM is to design an FIR linear filter with L filter coefficients $\{w_1, w_2 \ldots w_L\}$, denoted by L-dimensional vector $w = (w_1, w_2 \ldots w_L)^T$ that minimizes the filter output power subject to the following constraint

$$\mathbf{d}^T \mathbf{w} = \sum_{l=1}^{L} d_l w_l = 1. \tag{1}$$

It is worth noting that the constant one in Eq. (1) can be replaced by any scalar c [14]-[15].

Let y_i denote the output of the designed FIR filter resulting from the input $\mathbf{r}_i$. Then y_i can be written as

$$y_i = \sum_{l=1}^{L} w_l r_{il} = \mathbf{w}^T \mathbf{r}_i = \mathbf{r}_i{}^T \mathbf{w}. \tag{2}$$

Therefore, the average output power produced by the observation set S and the FIR filter with coefficient vector $\mathbf{w} = (w_1, w_2 \ldots w_L)^T$ specified by Eq. (2) is given by

$$\begin{aligned} \frac{1}{N}\left[\sum_{i=1}^{N} y_i^2\right] &= \frac{1}{N}\left[\sum_{l=1}^{L} \left(\mathbf{r}_i^T \mathbf{w}\right)^T \mathbf{r}_i^T \mathbf{w}\right] \\ &= \mathbf{w}^T \left(\frac{1}{N}\left[\sum_{i=1}^{N} \mathbf{r}_i \mathbf{r}_i^T\right]\right) \mathbf{w} \\ &= \mathbf{w}^T R_{LxL} \mathbf{w}, \end{aligned} \tag{3}$$

where $R_{LxL} = \frac{1}{N}\left[\sum_{i=1}^{N} \mathbf{r}_i \mathbf{r}_i^T\right]$ turns out to be the $L \times L$ sample autocorrelation matrix of S.

Minimizing Eq. (3) with the filter response constraint $\mathbf{d}^T \mathbf{w} = \sum_{l=1}^{L} d_l w_l = 1$ yields

$$\min_{w}\left\{\frac{1}{N}\left[\sum_{i=1}^{N} y_i^2\right]\right\} = \min_{w}\left\{w^T R_{LxL} w\right\} \tag{4}$$

subject to $d^T w = 1$.

The solution to Eq. (4) was shown in [15]-[16] and called Constrained Energy Minimization (CEM) classifier with the weight vector w* given by

$$\mathbf{w}^* = \frac{R_{LxL}^{-1}\mathbf{d}}{\mathbf{d}^T R_{LxL}^{-1}\mathbf{d}} . \tag{5}$$

It is worth noting that unlike array processing where the number of snapshots (i.e., observations) is generally greater than the number of sensors L (i.e., $N \gtrsim L$), the intrinsic dimensionality of a hyperspectral image, q may be sometimes less than the data dimensionality L. Under this circumstance, the sample autocorrelation matrix $R_{L\times L}$ is not full rank. As a result, calculating the inverse of $R_{L\times L}$ in Eq. (3) can be a problem. One way to resolve this is to use singular value decomposition to find the intrinsic dimensionality q so that $R_{L\times L}$ can be reduced to $\tilde{R}_{LxL} = \tilde{V}\Lambda\tilde{V}^T$ where $\tilde{V} = \left(\tilde{v}_1, \tilde{v}_2 \ldots \tilde{v}_q\right)$ is an eigenmatrix, $\tilde{v}_k$ is the L-dimensional vector corresponding to the k-th eigenvalue λ_k, $\Lambda = diag\{\lambda_1, \lambda_2 \ldots \lambda_q\}$ is a diagonal matrix with eigenvalues as diagonal elements. Using this eigen-decomposition, the inverse of $\tilde{R}_{LxL} = \tilde{V}\Lambda\tilde{V}^T$ can be found by $\tilde{R}_{LxL}^{-1} = \tilde{V}\Lambda^{-1}\tilde{V}^T$ [12].

3. Experimental results

In this section, we present a series of experiments using MR images of the brain to evaluate the effectiveness of CEM. The images used in the experiment were acquired from a patient with abnormal physiology (shown in Fig. 1) using four bands with resolution 8-bit gray level and 256 by 256 pixels. T1-weighted and T2-weighted images were acquired for band one and two. PD-weighted and Gd-DTPA images were acquired for band three and four.

The radiance spectra of cerebral tissues used to produce the CEM classification operator were obtained directly from the MR images and certified by expert radiologists. Fig. 2 shows the radiance spectrum, which was used to construct CEM classification operators. The first operator used the gray matter spectrum as the desired target. The desired target spectra of the second, the third and the fourth operators were white matter, cerebral spinal fluid and tumor. These operators were applied to each pixel of the brain MR images to segment and classify the desired target. Fig. 3 demonstrates the classification results of the cerebral tissue, with gray matter in Fig. 3(a), white matter in Fig. 3(b), cerebral spinal fluid in Fig. 3(c) and tumor in Fig. 3(d). As far as computing saving is concerned, the segmentation results in Fig. 4 were produced using the autocorrelation matrix without background mixed vector. This only uses 17683 mixed pixel vectors for multiplication while the original images requires 65536 multiplication's. The results show that the computation load is significantly reduced. As shown in Fig. 3 and Fig. 4, the CEM technique was able to correctly segment the MR images into the desired target signature of cerebral tissue.

4. Conclusion

Brain MR images segmentation is the critical step in the analysis of brain pathology. In this paper, we present a Constrained Energy Minimization (CEM) approach to desired target signature detection and classification of brain MR images. The idea of CEM is to consider the MR image classification problem as an array-processing problem where each sensor represents one spectral band. Since the target signature is the only signature that is of interest, an adaptive filter can be designed to pass the desired target with the specific gain so that the filter output resulting from an unknown source can be minimized. Experimental results have shown that the CEM technique was able to correctly classify the cerebral tissue into four-image gray matter, white matter, cerebral spinal fluid and tumor.

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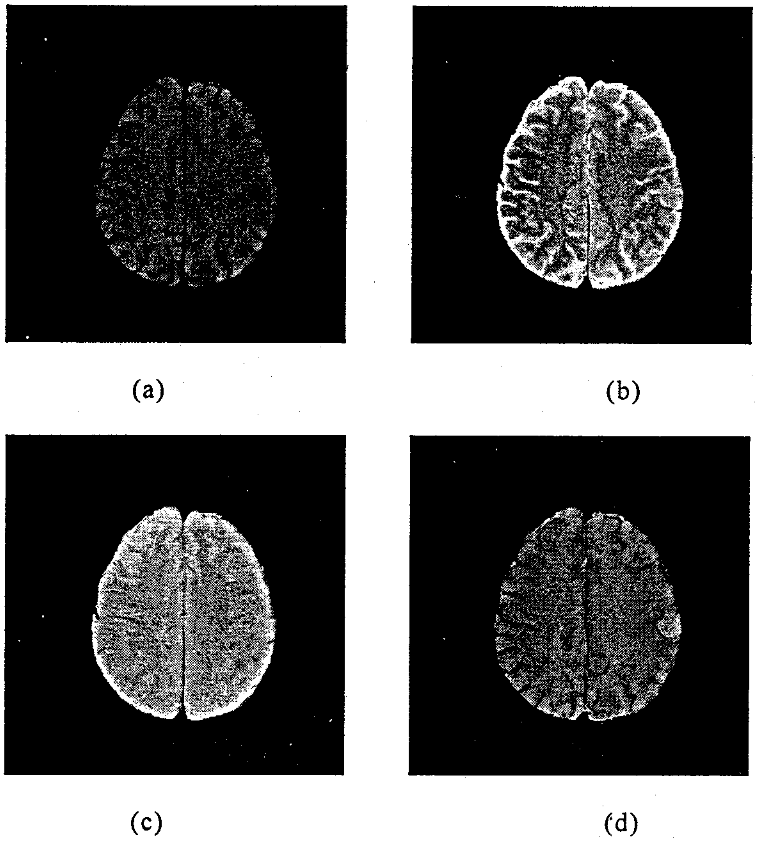


Fig. 1. The MR images of the brain. Axial section. (a) T1-weighted image; (b) T2-weighted image; (c) Proton density image; (d) Gd-DTPA

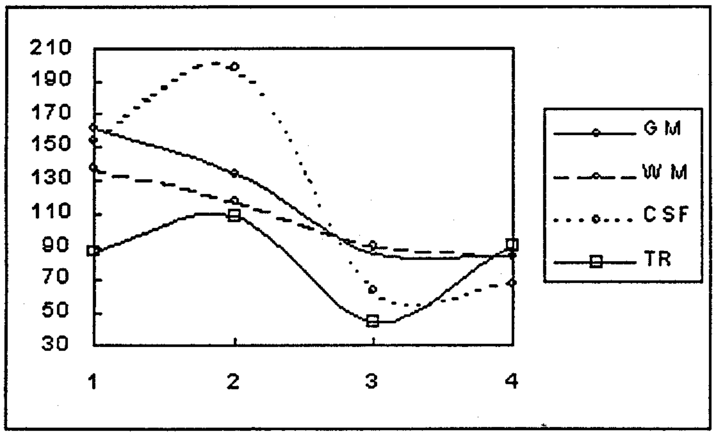


Fig. 2. Four bands radiance spectrum.

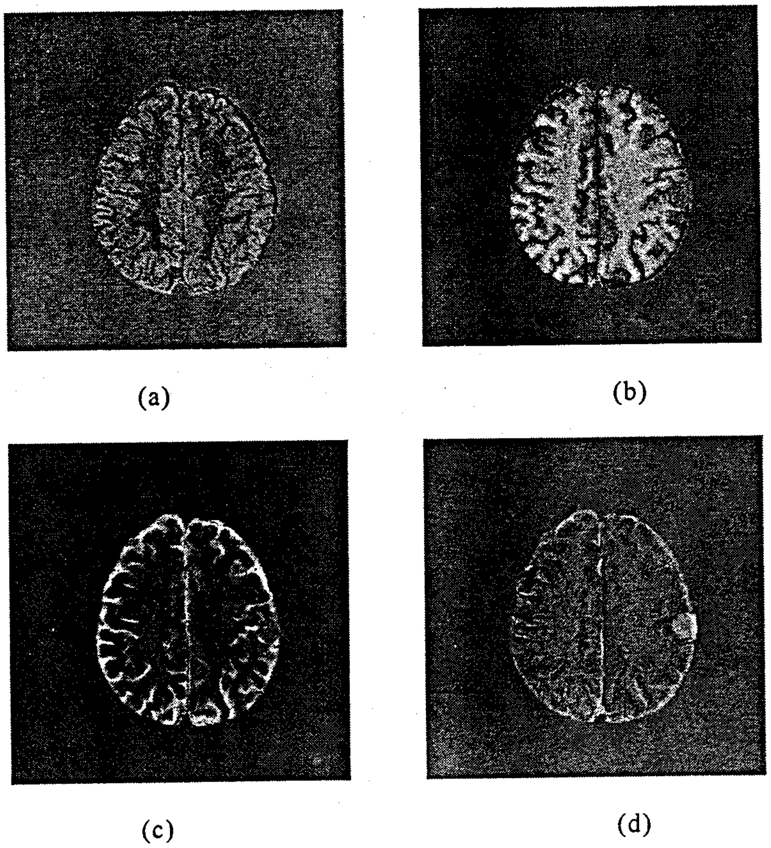
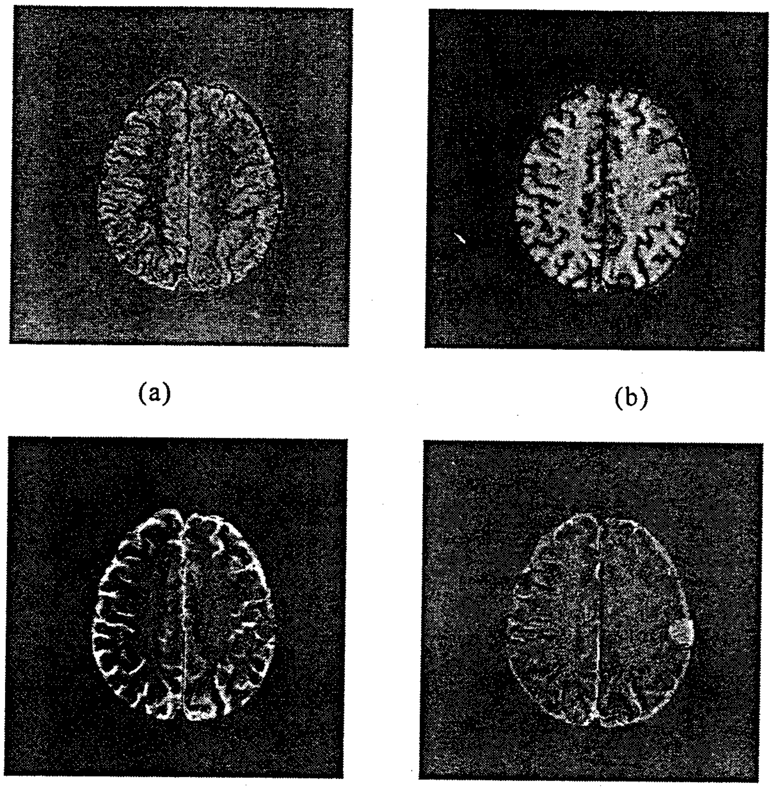


Fig. 3. Classification results of CEM . (a) gray matter; (b) white matter; (c) cerebral spinal fluid, (d) tumor.



(a) (b) (c) (d)

Fig. 4. Classification results of CEM using the autocorrelation matrix without background. (a) gray matter; (b) white matter; (c) cerebral spinal fluid, (d) tumor.

大腦磁振影像的自動腫瘤分割技術之研究

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摘要

在這篇論文中，我們提出了一個新方法，可使腫瘤從腦部的多頻譜磁振影像(Magnetic Resonance, MR)內給分類出來，這些磁振影像的組成是由三個磁振參數，質子密度(Proton Density, PD)，T1 分量(Weighted)和 T2 分量影像，經過多頻譜分析所處理出來的。我們提出的這個方法，稱爲抑制能量最小化法(Constrained Energy Minimization, CEM)，被研發於[12]內，認爲在所知道的領域中，把期望的特徵給分類出來，這方法所使用的基礎，就是矩陣運算中的最小化變異數無雜訊響應(Minimum Variance Distortionless Response ,MVDR)，CEM 將多頻譜 MR 影像視爲一個矩陣處理的問題，在這問題中的每一個觀察值都代表一個頻譜頻帶(Spectral Band)，再使用有限脈衝響應濾波器(Finite Impulse Response ,FIR)將輸出功率做最小化處理，使期望的特徵被強制到一個特定的增益。此方法已經由數個實驗所得證，實驗結果顯示出大腦組織正確地被分割爲四張影像，腦瘤(Tumor)、灰質(Gray Matter)、白質(White Matter)以及腦脊髓液(Cerebral Spinal Fluid ,CSF)，這些都象徵了這個方法是非常有用的。另外，對於計算所花的時間而言，實驗結果也顯示出繁雜計算的改進處。

關鍵字：抑制能量最小化法(CEM)，磁振影像(MRI)，分類法，大腦影像，腫瘤