Minimum Variance Distortionless Response Beamforming for Tumor Segmentation in MRI

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Abstract

Image classification it generally requires a priori knowledge about the objects to be classified. In this paper, we present a new method to segment tumor in multispectral magnetic resonance (MR) images of the human brain. The proposed approach, called Minimum Variance Distortionless Response beamforming (MVDR) was introduced in [15] where only the knowledge of the desired signature to be classified was required. It was a special case of Linearly Constrained Minimum Variance Beamforming (LCMV) in array processing. MVDR 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. That is the response of the beamformer is constrained to equal unity at the electrical angle. 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 –– Minimum Variance Distortionless Response (MVDR), Magnetic resonance imaging, Classification, Brain images, Tumor.

1. Introduction

Nuclear magnetic resonance (NMR) has recently developed as a versatile technique in many fields such as chemistry, physics, engineering because its signals provide rich information about material structures that involve the nature of a population of atoms, the structure of their environment, and the way in which the atoms interact with environment [1]. When NMR is applied to human anatomy, NMR signals can be used to measure the nuclear spin density, the interactions of the nuclei with their surrounding molecular environment and those between close nuclei, respectively. It produces a sequence of multiple spectral images of tissues with a variety of contrasts using three magnetic resonance parameters, spin-lattice (T1), spin-spin (T2) and dual echo-echo proton density (PD). By appropriately choosing pulse sequence parameters, echo time (TE) and repetition time (TR) a sequence of images of specific anatomic area can be generated by pixel intensities that represent characteristics of different types of tissues throughout the sequence. As a result, Magnetic Resonance Imaging (MRI) becomes a more useful image modality than X-ray computerized tomography (X-CT) when it comes to analysis of soft tissues and organs since the information about T1 and T2 offers a more precise picture of tissue functionality than that produced by X-CT [2].

One potential application of MRI in clinical practice is the brain parenchyma classification and segmentation of normal and pathological tissue. It is the first step to address a wide range of clinical problems. By means of the volume, shapes and region distribution of the brain tissue, one can find the abnormalities that are commonly related to the conditions of heterotopias, lissencephaly, brain atrophy, and cerebral infarction. Over the past years many computer-assisted methods have been reported [1]-[11] such as neural networks [5]-[9], hybrid methods [10], knowledge-based techniques [11], etc. For example, neural networks have demonstrated their superior performance in segmentation of brain tissue to classical maximum likelihood methods; hybrid methods have shown a promise by combining imaging processing and model-based techniques in segmentation [10]; knowledge-based techniques allows one to make more intelligent classification and segmentation decisions [11].

In image classification it generally requires a priori knowledge about the objects to be classified. Although it can be done in an unsupervised fashion, the results are generally not so good as supervised methods. It will be even worse if the objects are relatively small or the image background varies with pixel-by-pixel. Obtaining such prior information is not realistic in many practical applications. In this paper, we present a new approach to MRI classifications, called Minimum Variance Distortionless Response (MVDR) Beamforming, which does not requite background information. More specifically, the only working knowledge for MVDR is the desired object of interest. MVDR discard all other information. This is significant advantage in the case when an image contains unknown and unidentified objects. MVDR assumes that the direction of arrival from the desired signal is known a priori. Then it designs an adaptive filter to pass the desired signal with a specific gain so that the filter output resulting from unknown sources such as undesired signals and unwanted interferers can be minimized. Where the specific gain was chosen to be unity.

The remainder of this paper is organized as follows. Section II describes the Minimum Variance Distortionless Response (MVDR) Beamforming approach. Section III conducts a set of experiments to evaluate the effectiveness of MVDR in classification performance when MR images are used for analysis. Section IV concludes with some comments on the results achieved.

2. Minimum Variance Distortionless Response (MVDR) Beamforming Approach

Basically, MVDR uses a finite impulse response (FIR) filter to constrain the desired object signature by using unity as a specific gain while minimizing the filter output energy. MVDR was developed for array processing [12]-[16] with the desired object interpreted as the direction of arrival from a desired signal. It can be derived as follows

Let *y(n)* denote the output of the designedlinear transversal filter resulting from the input *r(n-l)* and w is the respective tap weight and *l = 0,1,...,L-1*. Then *y(n)* can be written as

$$y(n) = \sum_{l=0}^{L-1} w_l^* r(n-l) \tag{1}$$

where asterisk denote complex conjugation. For special case of a sinusoidal excitation r(n) can be as $e^{-jf_0 l}$ where ϕ is the electrical angle denoted the direction of arrival. Then y(n) can be rewritten as

$$y(n) = r_0(n) \sum_{l=0}^{L-1} w_l^* e^{-jf_0 l} \tag{2}$$

where $\boldsymbol{r_0}$ (n) is the first electrical signal treated as the point of reference. The objective of the constrained optimization problem is to minimize the variance of the beamformer output subject to follow constraint

.

$$\sum_{l=0}^{L-1} w_l^* e^{-jf_0 l} = g \tag{3}$$

It is worth noting that the constraint *g* in Eq. (3) can be replace by unity. The constrained optimization problem can be solved by the method of Lagrange multipliers. It combines two parts of constrained optimization problem is given by

$$J = \underbrace{\sum_{l=0}^{L-1}\sum_{k=0}^{L-1} w_l^* w_k r(k-l)}_{\text{output power}} - \underbrace{\mathrm{Re}\left[l^* \left(\sum_{l=0}^{L-1} w_l^* d_l - g \right) \right]}_{\text{linear constraint}} \tag{4}$$

The solution to Eq. (4) by minimizing the output power and subject to the constraint was called Minimum Variance Distortionless Response (MVDR) Beamforming filter with the weight vector $\mathbf{w}_o$

given by

$$\mathbf{w}_o = \frac{\mathbf{R}^{-1}\mathbf{d}(f_0)}{\mathbf{d}^H(f_0)\mathbf{R}^{-1}\mathbf{d}(f_0)} \tag{5}$$

where $\mathbf{R}$ is *L-by-L* correlation matrix, and $\mathbf{w}_o$ is the *L-by-1* optimum weight vector of the constrained beamformer. The *L-by-1* desired target vector $\mathbf{d}(f_0)$ is defined by

$$\mathbf{d}(f_0) = [1, e^{-jf_0}, \ldots, e^{-j(L-1)f_0}]^T \tag{6}$$

3. Experimental results

A set of multispectral MR brain images was used to evaluate the performance of OSP and UOSP. It consists of MR images 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 slice thickness of all MR images are 2mm and axial section were taken from Signa 1.5T SYS#GEMSOW. All experiments were under supervision of a neuroradiologist.

The radiance spectra of four cerebral tissues, gray matter (GM), white matter (WM), cerebral spinal fluid (CSF) and tumor used for MVDR are shown in Fig. 2. All spectra were extracted directly from the MR images and verified by experienced radiologists. Fig.3 show the classification results of MVDR based on the four images in Fig. 1 where the images labeled by (a), (b), (c) and (d) were generated respectively by using GM, WM, CSF and tumor as desired signatures **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. Fig. 5 shows the classification results using the autocorrelation matrix with only undesired pixels. It even only uses 2 mixed pixel vectors for multiplication. The results show that the computation load is significantly reduced. As shown in Fig. 3, Fig. 4 and Fig. 5, the MVDR technique was able to correctly segment the MR images into the desired target signature of cerebral tissue. As a final comment, in order to evaluate MVDR in all aspects only one representative MR image sequence was studied for experiments in this paper. In fact, more experiments were also conducted for performance evaluation. The results draw similar conclusions.

4. Conclusion

Brain MR images segmentation is the critical step in the analysis of brain pathology. In this paper, we present a Minimum Variance Distortionless Response (MVDR) Beamforming approach to desired target signature detection and classification of brain MR images. MVDR views an MR image sequence as a multispectral image cube with each pixel represented by spectral pixel vector. By considering the image cube as a whole, MVDR is able to capture both spectral and spatial correlations for classification. The major advantage of MVDR is that no background information is required. The idea of MVDR 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 MVDR technique was able to correctly classify the cerebral tissue into four-image gray matter, white matter, cerebral spinal fluid and tumor indicating the promising possibilities of this method.

References

[1] B. Johnston, M. S. Atkins, B. Mackiewich, and M. Anderson, "Segmentation of Multiple Sclerosis Lesions in Intensity Corrected Multispectral MRI," *IEEE Transactions on Medical Imaging*, vol. 15, no. 2, pp. 154-169, April 1996.

[2] M. Stella Atkins and Blair T. Mackiewich, " Fully Automatic Segmentation of Brain in MRI," *IEEE Transactions on Medical Imaging*, vol. 17, no. 1, pp. 98-107, February 1998.

[3] Atam P. Dhawan, Aleksandar Zavaljevski, Alok Sarwal, Walliam S. Ball, "A system for MRI brain image segmentation," *18th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, pp. 732-733 Amsterdam 1996.

[4] Laurent Verard, Jalal Fadili, Su Ruan, and Daniel Bloyet, "3D MRI segmentation of brain structures," *18th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, pp. 1081-1082 Amsterdam 1996.

[5] Wilburn E.Reddick, John O. Glass, Edwin N. Cook , T. David Elkin, and Russell J. Deaton, "Automated Segmentation and Classification of Multispectral Magnetic Resonance Images of Brain Using Artificial Neural Networks," *IEEE Transactions on Medical Imaging*, vol. 16, no. 6, pp. 911-918 December 1997.

[6] Javad Alirezaie, M. E. Jernigan and C. Nahmias "Automatic Segmentation of Cerebral MR Images using Artificial Neural Networks," *IEEE Transactions on Nuclear Science*, vol. 45, no. 4, pp. 2174-2182, August 1998.

[7] J.S. Lin, R.M. Chen, Y.M. Huang, "Medical image segmentation using mean field annealing network," *IEEE International Conference on Image Processing*, vol. 2, pp. 855-858, October 1997.

[8] J.S. Lin, K.S. Cheng, C.W. Mao, "Multispectral magnetic resonance images segmentation using fuzzy Hopfield neural network," *International Journal of Biomedical Computing*, pp. 205-214, August 1996.

[9] J.S. Lin, K.S. Cheng, C.W. Mao, "Modified Hopfield neural network with fuzzy c-means technique for multispectral MR image segmentation," *IEEE International Conference on*

Image Processing, vol. 1, pp. 327-330, September 1996.

[10] M. Stella Atkins and Blair T. Mackiewich, “ Fully Automatic Segmentation of Brain in MRI,” *IEEE Transactions on Medical Imaging*, vol. 17, no. 1, pp. 98-107 February 1998.

[11] Matthew C. Clark, Lawrence O. Hall, Dmitry B. Goldgof, Robert Velthuizen, F. Reed Murtagh, and S. Silbiger, “Automatic Tumor Segmentation Using Knowledge-Based Techniques,” *IEEE Transactions on Medical Imaging*, vol. 17, no. 2, pp.187-201 April 1998.

[12] J.C. Harsanyi, Detection and Classification of Subpixel Spectral Signatures in Hyperspectral Image Sequences, Ph.D. dissertation, Department of Electrical Engineering, University of Maryland Baltimore County, Baltimore, MD, August 1993.

[13] Frost III, "An algorithm for linearly constrained adaptive array processing," *Proc. IEEE*, vol. 60, pp. 926-935, 1972

[14] B.D. Van Veen, and K.M. Buckley, "Beamforming: a versatile approach to spatial filtering," *IEEE ASSP magazine*, 4-24, April 1988

[15] S. Haykin, *Adaptive Filter Theory*, 3rd ed., NJ: Prentice-Hall, 1996.

[16] W. Farrand, W., and J.C. Harsanyi, "Mapping the distribution of mine tailing in the coeur d'Alene river valley, Idaho, through the use of constrained energy minimization technique," Remote Sensing of Environment, vol. 59, pp. 64-76, 1997.

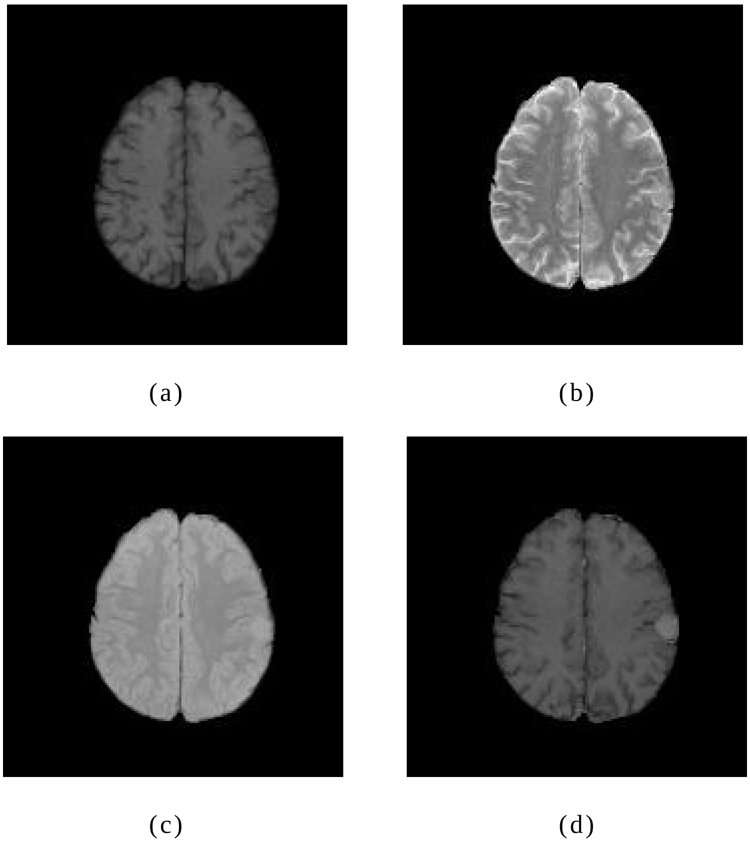


Fig. 1. The MR images of the brain. Axial section. (a) T1-weighted image; (b) T2-weighted image; (c) Proton density image; (d) Gd -DTPA

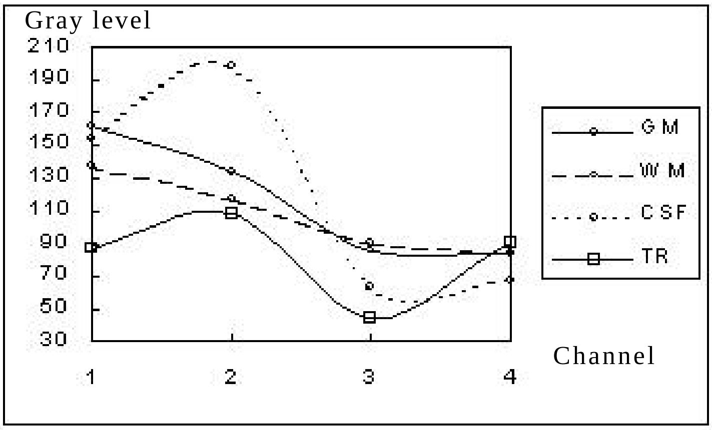
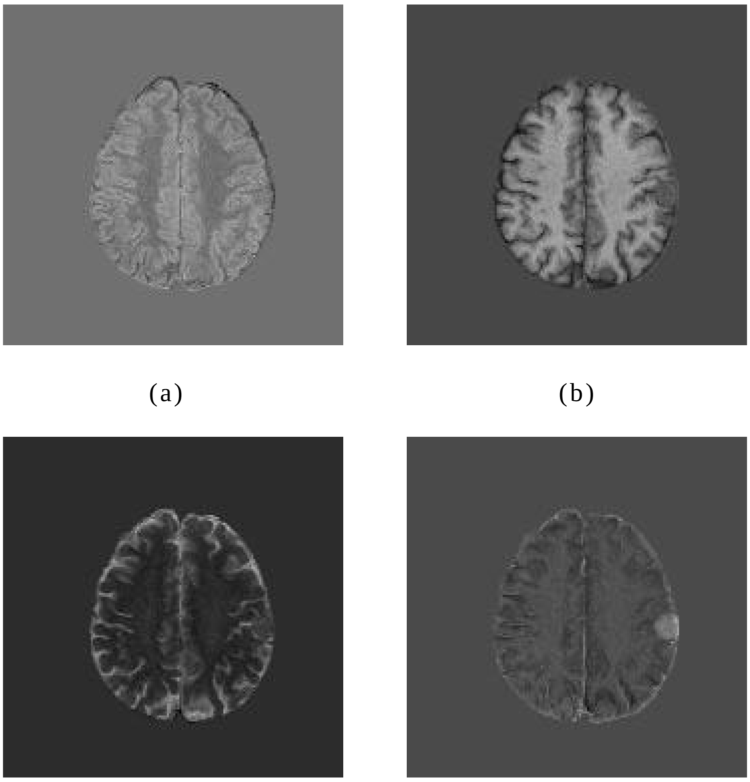
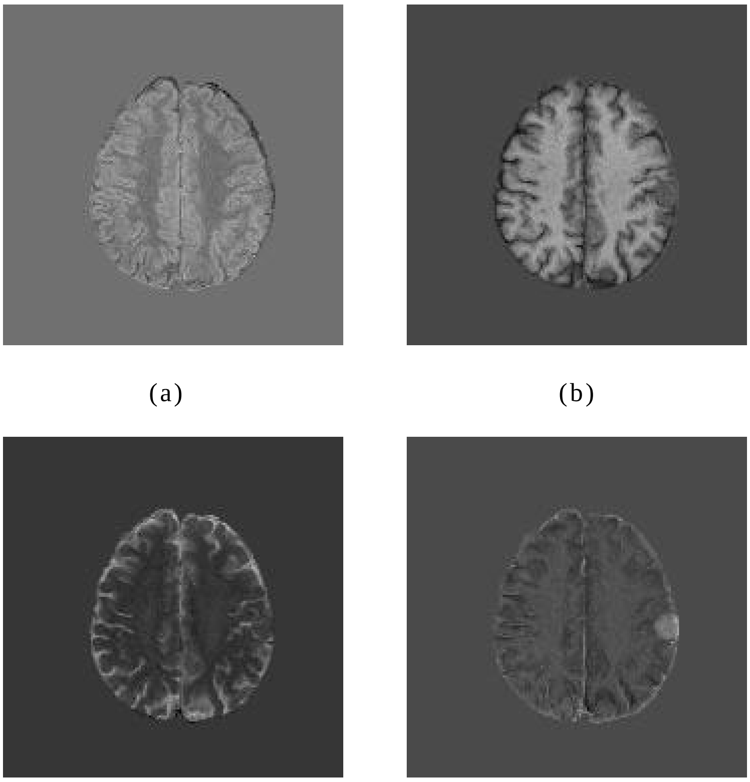


Fig. 2. Four bands radiance spectrum.



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

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



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

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

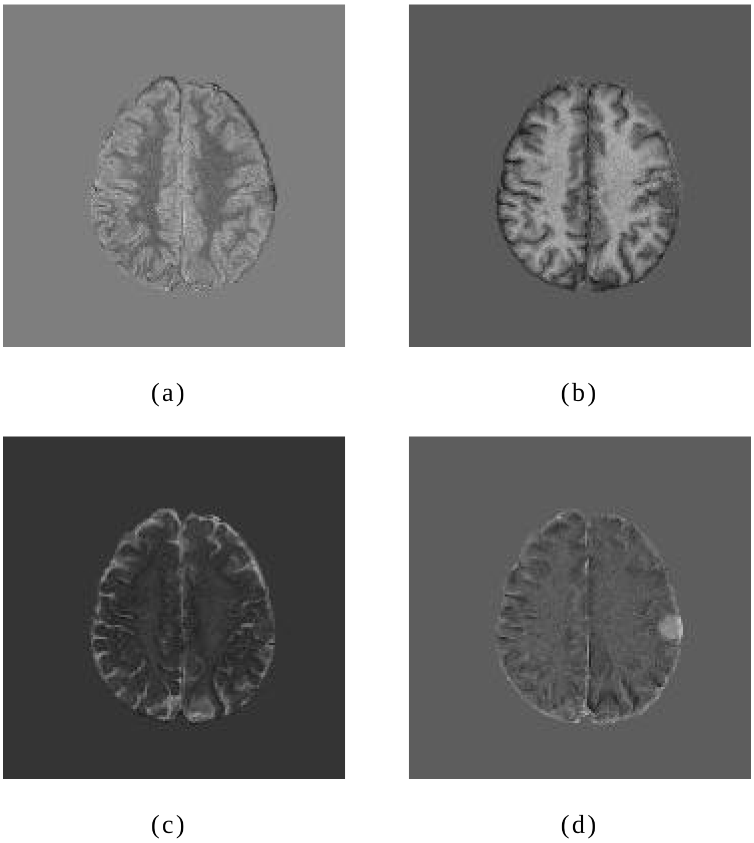


Fig. 5. Classification results of MVDR using the autocorrelation matrix with only undesired pixels. (a) gray matter; (b) white matter; (c) cerebral spinal fluid, (d) tumor.

最小化變異數無雜訊響應光束形成法在大腦磁振影像的腫瘤分割應用

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摘要

在影像分類法中，總是需要一些預先知道的目標知識才能被應用於分類上，在這篇論文中，我們提出了一個新方法，可把人類大腦中的腫瘤從多頻譜磁振影像(Magnetic Resonance, MR)內給分類出來，這個方法稱作最小化變異數無雜訊響應(MVDR)光束形成法[15]，它只需知道期望的特徵(Desired Signature)資訊就可被分類出來。MVDR光束形成法是線性抑制最小化變異數(LCMV)光束形成法於排隊理論(Array-Processing)中的一個特例，它將磁振影像當成排隊理論的問題，在排隊理論裡的每一個感測器都被當成是一個頻譜(Spectral Band)，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，並使期望的特徵被限制到一個特定的增益，在光束形成法中即在特定的相位角時將輸出設為一。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為四張影像，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：最小化變異數無雜訊響應(MVDR) 光束形成法，磁振影像(MRI)，分類法，大腦影像，腫瘤