Magnetic Resonance Image Classification via Over-Complete Independent Component Analysis and Active Support Vector Machines

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ABSTRACT

Independent component analysis (ICA) has recently received considerable interest in applications of magnetic resonance (MR) image analysis. However, the ICA used for MR image analysis is generally over-complete in the sense that the number of images is usually less than the number of signal sources to be blindly separated. As a result, more than one brain tissue clusters may be separated and forced into a single independent component (IC) so that these brain tissues substances present in a particular IC cannot be discriminated one from another. In this paper, we proposed an over-complete ICA (OC-ICA) method in conjunction with spatial domain-based classification in order to achieve better classification in each single independent component (IC) as well as discrimination of brain tissue substances.

INTRDOCUTION

ICA has shown great promise in the analysis of functional magnetic resonance imaging (fMRI) [1]. As the samples for fMRI are collected along a temporal sequence, the number of samples, denoted by L is usually greater than the sources to be separated, denoted by p, the ICA used for fMRI is generally under-complete in the sense that the ICA deals with under representation of a mixed model. Recently, a new application of ICA in brain MR image analysis was investigated to perform image evaluation for a particular tissue such as white matter (WM), gray matter (GM) and tumors [2]. In this case, the samples used for MR image analysis are actually a stack of images acquired by different pulse sequences to represent three tissue characteristics of spin-lattice (T1), spin-spin (T2) and proton density (PD). The number of signal sources to be separated, p is greater than the number of different combinations of pulse sequences, L, thus, the ICA becomes an under-determined system with $L < p$. As a result, more than one brain tissue clusters may be separated and forced into a single independent component (IC) so that these brain tissues substances present in a particular IC cannot be discriminated one from another. In order to resolve this issue, this paper presents an approach which implements the over-complete ICA (OC-ICA) in conjunction with spatial domain-based classification so as to achieve better classification in each of ICA-demixed ICs.

METHODS

The key idea of the ICA assumes that data are linearly mixed by a set of separate independent sources and these signal sources can be demixed according to their statistical independency measured by mutual information [1]. Let **x** be a mixed signal source vector expressed by

$$\mathbf{x} = \mathbf{A}\mathbf{s} \qquad (1)$$

where **A** is an $L \times p$ mixing matrix and **s** is a p-dimensional signal source vector needed to be separated. According to system theory, the linear system equation described by (1) is actually an over-determined system, in which case there exits no solution to (1). In order to mitigate the issue that more one signal source accommodated in a single IC, a feature extraction-based classification technique called Support Vector Machine (SVM) is included as a post OC-ICA processing technique to classify substances of interest. The SVM is designed to find an optimal hyperplane that separates two classes of data samples as farther as possible by maximizing the margin of separation between classes and the hyperplane. The SVM was originally developed by Vapnik based on statistical learning theory [3].

Experiments

The experiments were conducted to substantiate the utility of our proposed OC-ICA with classification of the simulated and real MR images. MR simulated T1, T2, and PD weighted brain images are available on website with the parameters of 5 mm slice thickness, 0% noise level, and 0% intensity non-uniformity [4].The real MR brain images were acquired from one normal volunteer by a whole body 1.5-T MR system (Sonata, Siemens, Erlangen, Germany), consisted of axial spin echo T1 weighted images (TR/ TE = 400/9ms), and dual fast spin echo images (TR/ TE = 4000/11, 91ms, echo-train-length =15). Other imaging parameters were slice thickness = 6mm, matrix = 256x256, FOV = 24cm, NEX = 2.

RESULTS

Since the ICA uses random initial projection vectors, the final results of ICs are different, as shown in Figure 1(b)-(c). The proposed OC-ICA coupled with a feature extraction-based classification technique as post OC-ICA processing has yielded two major advantages. It makes use of the ICA to linearly transform three band MR images into three statistically independent component images so that these three ICA-generated independent components (ICs) can be stacked one atop another to form a new image cube which are spectrally and statistically independent in ICs. As a result, brain tissue substances appear in these three component images are supposed to be statistically independent or least dependent from a statistical point of view and can be classified separately and individually to avoid potential confusion, as Figure 1(e)-(f).

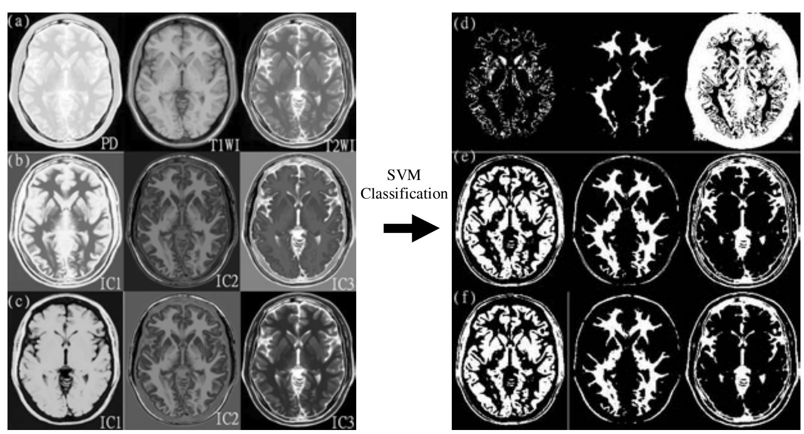

Figure1 (a) The simulated brain images; **(b)** and **(c)** the three IC images; **(d)** SVM classification images without ICA transform; **(e)** and **(f)** SVM classification images with ICA transform.

DISCUSSIONS and CONCLUSIONS

The ICA is a versatile technique and has shown great success in many applications. This paper provides such an example where a direct application of the ICA to MR image analysis without taking precaution may produce unsuccessful results, and also explores an application of the over-complete ICA (OC-ICA) to MR image analysis. In the first stage, the ICA separates distinct objects into ICs in the sense of statistical independency, then followed by a feature extraction-based classification technique in the second stage to perform target substance discrimination compared to previous approaches which extract features directly from MR images in one-shot operation. Results show that the OC-ICA implemented with classification can be very effective provided the training samples are judiciously selected.

References

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