Classification of Alzheimer’s from T2 Trans-Axial Brain MR Images: A Comparative Study of Feature Extraction Techniques

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ABSTRACT

Alzheimer’s disease is the most common form of dementia occurring in the elderly persons. Its early diagnosis may help in providing proper treatment. To date, there is no appropriate technique available to automatically classify it using MR brain images. In this work, first-and-second-order-statistics (FSOS) was employed for classification of Alzheimer’s from T2 trans-axial brain MR images. Although FSOS is a simple and well known feature extraction technique, it is not yet explored for Alzheimer’s classification. Performance of FSOS was compared with the state-of-the-art feature extraction techniques. Five commonly used classifiers were employed to build decision models. The performance of the models was evaluated in terms of sensitivity, specificity, accuracy, F-measure, training, and testing time. These models were built with varying number of training samples. Results showed that FSOS outperforms all the other existing feature extraction techniques in terms of all the considered performance measures. This was also validated by a statistical test. Interestingly, it was found that FSOS gives high performance irrespective of the choice of classifier and it works well even on small available number of samples, which is usually desired for all real time problems.

Keywords: Discrete Wavelet Transform, Feature Extraction, First and Second Order Statistics, Gabor Transform, Magnetic Resonance Imaging, Slantlet Transform

INTRODUCTION

Alzheimer’s disease (AD) is the most commonly found neurological disorder and common cause of dementia for the elderly persons. It causes mental disorder and disturbances in brain functions such as memory, language skills, and perception of reality, time and space. World Health Organization and the U.S. National Institute on Aging highlighted that its early and
accurate diagnosis may help in development of appropriate treatment.

Alzheimer’s Association Neuroimaging Workgroup (Albert et al., 2004) emphasized usage of image analysis techniques for its better diagnosis. Among various imaging modalities, magnetic resonance imaging (MRI) is the most preferred technique since it is non invasive with no side effects of harmful rays. It is also suitable for the internal study of human brain, to retrieve better information about soft tissue anatomy. However, there is a huge MRI repository, which makes the task of manual interpretation difficult. Hence computer aided analysis and diagnosis of MRI brain images has drawn the attention of research community in recent past.

In literature, several approaches have been suggested to distinguish AD patients from normal subjects using anatomical MRI images. These approaches involve two main components: (i) feature extraction, and (ii) classification. Several feature extraction techniques and classifiers have been suggested in this endeavor. Bagci and Bai (2007) extracted features using gabor transform, a special variant of short time fourier transform (STFT), which has selective frequency and orientation properties. It extracts both frequency and time information from a non stationary signal with the use of fixed size window. They constructed a feature vector of length 4096 and evaluated the decision system using two classifiers namely linear support vector machine (SVM-L) and support vector machine with radial kernel (SVM-R). Chaplot, Patnaik, and Jagannathan (2006) determined features using gabor transform and applied SVM-L and SVM-R. Dahshan, Hosny, and Salem (2010) suggested discrete wavelet transform (DWT) for feature extraction. Unlike fixed width window of STFT, DWT allows analysis of a signal at various levels of resolution using both low and high frequencies simultaneously. Chaplot, Patnaik, and Jagannathan (2006) determined 4761 features with level 2 decomposition using daubechies-4 (db4) wavelet and applied SVM-L and SVM-R. Dahshan, Hosny, and Salem (2010) constructed a reduced feature set by employing haar wavelet at level 3 and further reduced it to 7 features using principle component analysis (PCA). In their work, they employed levenberg–marquardt neural classifier (LMNC) and k-nearest neighbor (KNN). Maitra and Chatterjee (2006) built a smaller feature set of size 6 using slantlet transform (ST), a variant of DWT, and utilized LMNC.

It is well known (Jain, Duin, & Mao, 2000; Raudys, 2006) that the performance of a classifier depends upon three factors: the training sample size, number of features and classifier complexity. For the fixed training sample size, as the number of salient features increases, one obtains an initial improvement in performance, but after a critical value, further increase in the number of features results in the degradation of the performance. This phenomenon is referred to as peaking phenomenon (Hughes, 1968). Also, increase in the number of features results in increase in the number of unknown parameters of a classifier. This reduces reliability of the parameter estimation and consequently degrades performance of the classifier. Therefore, the number of training samples must be larger than the number of features for better prediction of classifiers.

However in literature, features extracted using gabor (Bagci & Bai, 2007) and wavelet (Chaplot, Patnaik, & Jagannathan, 2006) are quite large (of the order $10^3$) in comparison to available number of MRI samples (of the order $10^2$). Hence the learning model suffers from curse-of-dimensionality and may not be appropriate for diagnosis and prediction. So, there is a need to either reduce these large numbers of features or use a feature extraction technique which can directly provide a minimal set of salient features.

One such well-known and simple approach is based on first and second order statistics (FSOS) (Papoulis, 1991; Haralick, Shanmugan, & Dinstein, 1973) which provides a minimal set of salient features. Although FSOS has been used in many domains (Tang, Douglas, & Daniel, 2011; Karahaliou et al., 2008; Fairley, Georgoulasc, Mehta, Grayb, & Bliwisea, 2012), it is not explored in AD diagnosis using MRI.
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