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資訊科學與工程研究所

碩士論文

以貝氏定理為基礎之神經疾病磁振造影影
像電腦輔助評估系統

Computer-aided MRI Evaluation of Neurological
Diseases based on Bayes' Theorem

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Computer-aided MRI Evaluation of Neurological Diseases based on
Bayes' Theorem

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摘要

近年來，由於醫學影像分析技術的蓬勃發展，電腦輔助診斷系統也隨之成為研究的潮流。以往的診斷是依賴醫師們的專業判斷，但這樣的判斷會受限於醫師主觀的判斷，且較小不易被肉眼察覺的部分容易被忽略。此外，受測者需花費許多時間等待結果。因此，建造一套簡單且具高正確率的電腦輔助診斷系統可以客觀且省時的方式，提供醫師及受測者們參考的指標。目前已存在許多輔助診斷系統，但多數的系統僅提供絕對性的參考指標。而在我們提出的方法中，我們以機率值的方式呈現估測的結果，提供醫師及受測者一個具有程度差異的相對性指標。

在本研究中，我們將圖形識別(pattern recognition)的技術應用在建立輔助系統上。整個系統是由數個平行的分類模組所組成，且每一個分類模組單就針對一種特定疾病作分析。每一個分類模組的建立都需經由兩個步驟：特徵擷取(feature selection and extraction)與分類(classification)。首先，透過以體素為基礎的型態計量學(voxel-based morphometry, VBM)，找出某一特定疾病病患與正常人的腦部結構差異所在，並將這些具有鑑別力的特徵選取出來。再者，應用主要成分分析(principal component analysis)技術找到最合適的資料表示方式，並採用兩種方式篩選合適的主軸建構分類空間，分別稱為以變異量為基礎的主軸挑選方法(variance-based PC selection)及以鑑別力為基礎的主軸挑選方法(significant-based PC selection)。最後應用貝氏定理(Bayes' Theorem)配合非參數密度估測方法(nonparametric density estimation – Parzen Windows)，估測受測者罹患某種特定疾病的機率。

我們將此分類架構應用在脊髓小腦運動失調症(spinocerebellar ataxia type III, SCA3)及躁鬱症(bipolar disorder, BD)的研究中，且各用兩種主軸挑選方式皆各自建構對應的分類器。我們發現採用以鑑別力為基礎的主軸挑選方法所建構的分類器，能達到較好的系統效能，且其呈現的結果也較為合理一致。



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Abstract

Recently, the study of computer-aided diagnosis (CAD) becomes a trend of biomedical signal processing due to developments from medical image analysis technology. In the past, a diagnosis depends on doctors' judgments, is subjective to physicians and costs much time for subjects to get results. Moreover, subtle differences which reveal potential danger may be invisible to human eyes. Thus, a simple CAD system with high correct accuracy can supply an index sign for physicians and subjects in an objective and convenient way. Most of existent systems, however, provide an absolute prediction on a test subject. It means that the answer would be either yes or no. Therefore, we propose a probabilistic approach to tell doctors and test subjects probabilistic predictions which show the difference of degree.

In this thesis, we construct a computer-aided MRI evaluation system with statistical pattern recognition technology. The entire system is parallelly composed of several disease classification models and each classification model is aimed at classifying a particular disease. For each model, there are two processes: feature selection and extraction, and classification. Initially, locations where reveal significant anatomical discrepancy discovered by a voxel-based morphometric analysis (VBM) are picked out as distinguishable features for classification. Moreover, principal component analysis (PCA) is applied to find proper representations for those found features and some applicable PCs are chosen to establish a good classification space by two principal component (PC) selection methods. One is named as variance-based PC selection method and the other is significant-based PC selection method. Finally, the classification model predicts the possibility of a test subject to sicken with a particular disease by using Bayes' Theorem and a nonparametric density estimation, Parzen windows.

Our proposed classification framework was applied on spinocerebellar ataxia type III (SCA3) and bipolar disorder (BD) and two corresponding classification models were established separately. Both of two PC selection methods were used in each model. Thus,

there were two distinct classifiers in a model. In our experiments, we found that a classifier with significant-based PC selection method not only achieves a better performance but also has a more consistent result.



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