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MR Image texture analysis applied to the diagnosis of Alzheimer's Disease

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Abstract

Chapter 1

Intro

In this report we will examine MRI data of the hippocampus using image texture analysis and apply machine learning. We have XX normal controls and XX Alzheimer's Disease (AD) patients. They are split into a training set (XX control and XX AD) and a test set (XX control and XX AD).

We will be using two different texture analysis on the data, XX and the gray level co-occurrence matrix (GLCM). We will calculate the GLCM using two different methods, one in 2D that that runs along the z-axis with angel 90 and distance 1 (Change depending on the results, and more research might include multiple angles).Castellano[2] The other method is calles voxel-based GLCM in 3D space (VGLCM-TOP-3D), and is from the paper Voxel-Based Texture Analysis of the Brain (indsæt biblografi). We want to see if there is a difference between diagnostising a AD succesfully, by calculating the co-occurence matrix in 3D compared to 2D, and how well the GLCM methods work compared to XX. To do that we will use two different machine learning methods, k-NN and Gaussian mixture, based on each of the image texture models.

FiXme Note: citation

We will also try to replicate the analysis from MRfreeborough[1] and meanwhile tell if we can get better accuracy

1.1 Problem Definition

Is it possible to classify MRI data of the hippocampus into groups of healthy controls vs Alzheimer's patient, using a predefined set of image texture metrices, with an accuracy greater than 80%?

1.2 Alzheimer's Disease

About 70% of the risk is believed to be genetic, where other factors include head injuries, depression or hypertension. Magnetic[3]

1.3 Image texture analysis methods

1.3.1 Co occurrence matrix

Co occurence matrix is defined over an image to be the distribution values at a given offset.Bharati[4] With the co occurence matrix, we have matrix **C** defined over an $n \times m$ image, with $\Delta x, \Delta y$ being the parameterized offset, so

$$C_{\Delta x,\Delta y}(i,j) = \Sigma_{p=1}^{n} \Sigma_{q=1}^{m} \begin{cases} 1, & \text{if } I(p,q) = i \text{ and } I(p+\Delta x, q+\Delta y) = j \\ 0, & \text{otherwise} \end{cases}$$

1.4 Machine learning methods

1.4.1 K-nearest neighbors algorithm

k-NN for short is a method that is used for classification and regression. Where the output is a class and member of this class, and this object is classified by its neighbors. For instance, if we chose k to 1, then the object will be assigned to the class of the single nearest neighbor.

The algorithm consist of training examples, that are vectors in multidimensional space, with each its label. The most used distance metric is Euclidean distance.

The drawback of k-NN is that classification can be skewed in that way, that the more frequent class tend to dominate the prediction of new examples, because they tend to be common among the k-NN due to their large number.

The way we wish to implement the k-NN in matlab is, first we handle the data, then we will calculate the distance between two data instances and after that, we can locate k most similar data instances and generate a response from a set. After all this is done, we have to summarize the accuracy of predictions.

Chapter 2

Tools

2.1 Image texture (Co-occurrence)

2.2 Principal Component analysis

2.2.1 Application to images

2.3 Cross validation

2.4 K-nearest neighbors

2.5 K-means

Image texture PCA Principal Component Analysis Application to images Machine learning (Knn, Ann, Gaussian)

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Chapter 3

Optimizing

hvordan vi kan få den til at udregne det kun en gang i derivations for C_xminusy og C_xplusy

C_xminusy fik en forbedring på 97%

Appendices

Appendix A

Co occurrence matrix derivation features

$$C_x(i) = \sum_{j=1}^{N} C(i,j)$$

$$C_y(i) = \sum_{i=1}^{N} C(i,j)$$

$$C_{x+y}(k) = \sum_{\substack{i=1 \\ i+j=k}}^{N} \sum_{j=1}^{N}, \quad \text{k = 2, 3, ... , 2N}$$

$$C_{x+y}(k) = \sum_{\substack{i=1 \\ |i-j|=k}}^{N} \sum_{j=1}^{N}, \quad \text{k=0,1,...,N-1}$$

$$f_1 = \sum_{i=1}^{N} \sum_{j=1}^{N} \{C(i,j)\}^2 \qquad \text{(A.0.1)} \quad \boxed{\texttt{AngularSecond}}$$

$$f_2 = \sum_{n=0}^{N-1} n^2 \left\{C_{x+y}(k)\right\} \qquad \text{(A.0.2)} \quad \boxed{\texttt{Contrast}}$$

$$f_3 = \frac{\sum_{i=1}^{N} \sum_{j=1}^{n} ijC(i,j) - \mu_x\mu_y}{\sigma_x\sigma_y} \qquad \text{(A.0.3)} \quad \boxed{\texttt{Correlation}}$$

$$f_4 = \sum_{i=1}^{N} \sum_{j=1}^{N} (i-\mu)^2 C(i,j) \qquad \text{(A.0.4)} \quad \boxed{\texttt{Variance}}$$

$$f_5 = \sum_{i=1}^{N} \sum_{j=1}^{n} \frac{1}{1+(i-j)^2} C(i,j) \qquad \text{(A.0.5)} \quad \boxed{\texttt{InverseDiffer}}$$

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