3-D MRI Brain Scan Classification of Epilepsy versus Non-epilepsy

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Abstract

A 3-D classification method is presented for Magnetic Resonance Imaging (MRI) brain scan volumes of interest. The objective of the classification is to identify volumes that feature indicators of epilepsy against volumes that do not by considering the shape and size of the lateral (left and right) ventricles of the brain. The dataset used with respect to the reported experimentation comprised 210 3-D MRI brain scans of which 105 were from epilepsy patients and the remainder from healthy people. The classification is supported by two proposed point-series based representation techniques: (i) Disc and (ii) Spoke. The reported experimental results indicated that our proposed techniques can classify 3-D MRI brain scan data with a classification accuracy of up to 69.81%.

1 Introduction

Automated (or semi-automated) medical prediction is a challenging real world problem. The effective and efficient automated prediction of medical conditions is clearly of significant benefit especially with respect to the use of resources, even if used as a "first screening". The work presented in this paper is directed at the automated screening for epilepsy from Magnetic Resonance Imaging (MRI) brain scan volumes (although the work has clear application elsewhere). Epilepsy is a medical condition whereby nerve cell activity in the brain is disturbed; it causes abnormal behaviour accompanied by symptoms such as loss of consciousness or convulsions. There are various indicators for the cause of epilepsy, one is the shape and size of the ventricles contained in the brain [7]. This can be measured by manuel inspection of MRI scan data. MRI brain scan data consists of a sequence of 2-D "slices" in three planes: Sagittal (SAG), Coronal (COR), and Transverse (TRA). Collectively we refer to this set of slices as a *volume*. However, although tools exist to support manuel inspection (for example the Brain Voyager range of software products), the process is time consuming, challenging and error prone. Automation of the process therefore seems desirable.

This paper proposes the use of a machine learning approach, more specifically a classification approach. Classification is concerned with the automated allocation of labels to data using a piece of software known as a classifier; in our case the input is a description of the lateral ventricles and the labels are the set $\{epilepsy, \neg epilepsy\}$. However, the classification process also entails a number of challenges, the most significant of which are: (i) the production of the classifier and (ii) the mechanism for representing the input in such a way the key information is retained while at the same time ensuring tractability (the two challenges are related). Classifiers are typically generated using pre-labelled training data (we refer to

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this as *supervised learning*). There are various techniques where by classifiers can be learnt, in this paper we explore the use of two. So as to obtain a level of confidence in a generated classifier it is typically evaluated against pre-labelled test data.

The representation of the input data is a key part in the classifier generation process. The image representation will affect both the efficiency and effectiveness of the machine learning. In this paper, two representation techniques, referred to as the Disc-based and Spoke-based representations, are proposed. Both are point-series representation techniques in that they are designed to capture the boundary a Volume Of Interest (VOI) in terms of a series points which in turn can be conceptualised as a curve in 2-D space. Such curves can be used directly for classification purposes using (for example) a *k*NN (*k* Nearest Neigbour) process [3] which requires some form of similarity measure; in this paper we use the length of the shortest "warping path" generated using the well established Dynamic Time Warping (DTW) technique. Alternatively the curves can be processed further so that a *feature space* model is derived which will allow for the individual VOI to be represented in terms of a *feature vector*. In this paper we suggest the use of Hough "signature" extraction for this purpose. Feature vector representations are compatible with a number of "standard" classifier generation models, in this paper the Support Vector Machine (SVM) [2] model is used but any other form of classifier generation model may be equally well applicable. Both the Disc and Spoke based representations are described as well as the *k*NN and SVM classification processes, together with a full evaluation.

2 Point Seres Generation

From the above, two techniques for generating a point series representation are proposed, the Disc-Based technique and the Spoke Based technique. The input in both cases is a previously segmented description of the VOI (the lateral ventricles in our case). With respect to the evaluation presented later in this paper the authors used the *Bounding-Box* segmentation technique proposed and described in [10] together with a thresholding technique for noise removal. Other similar techniques would have sufficed however experiments conducted by the authors, and presented in [10], indicate that the Bounding-Box technique works well with respect to the lateral ventricles (a comparison was conducted against manually identified ventricles and a good correlation was found to exist). Essentially the segmentation results in a *zero-one* representation where voxels that are part of a VOI (the lateral ventricles) are marked with a 1 (black) and voxels that are not part of the VOI are marked with a 0 (white). The Disc-based technique is described in Sub-section 2.1 and the Spoke based technique in Sub-section 2.2 below.

2.1 Disc-based Representation Technique

The Disc-based representation technique is illustrated in Figure 1. A point series is generated by taking a series of measurements from the centroid of the VOI (the lateral ventricles) to each voxel located on the boundary of the VOI. This is achieved by iteratively moving a 2-D plane along the length of the VOI voxel by voxel along a selected axis. At each iteration the intersection between the plane and the VOI was identified and measurements taking from the centroid of the VOI to the the voxels located along the boundary of the intersection. With respect to the ventricles the intersection typically took the form of a "disc" shape, hence the name "Disc-based" representation. Whatever the case the measurements were then used to describe a 2-D curve with distance along the Y-axis and the sequential measurement identification number along the X-axis. In the case of the ventricles three such curves were generated one for each of the the three cardinal axes: Sagittal, Coronal and Transverse. A perceived disadvantage of the Disc-based technique is that a large number of points are generated giving rise to substantial curves which in turn might require considerable computational resource to process (it is desirable for screening to be conducted at time of consultation, thus in real time using the processing power available on standard desk top machines). Note also that the Disc-based technique, given a collection of segmented ventricles, will produce curves of different lengths (ventricles will be of different sizes) which is not ideal for comparison purposes. The Spoke based technique described in the following sub-section seeks to address this issue.

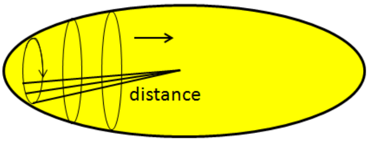

Figure 1: Disc-based point series generation

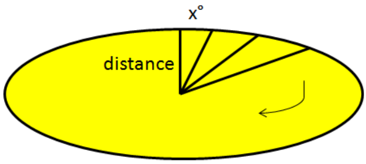

Figure 2: Spoke-based point series generation

2.2 Spoke-based Representation Technique

The spoke based point series generation technique is illustrated in Figure 2. The idea is to measure the distance from the centred to the VOI boundary only in the three cardinal planes (Sagittal, Coronal and Transverse in the case of our ventricles). This is achieved by considering each plane in turn and conceptually generate a set of "spokes" radiating out from the centroid, spaced at some angle of separation x°, and then measuring the distance from the centroid to where the spoke cuts the boundary of the volume (when the spoke reaches a back voxel followed by a white voxel). The result was again three point series, but in this case each point series contained fewer points than in the case of the Disc-based technique. In addition the curves will all be of the same length provided the same value of x is used through out

3 Classification

For classification purposes we require a training set of pre-labelled data (in our case a MRI brain scan dataset with each scan labelled as either *epilepsy* or $\neg$*epilepsy*. Point series (curves) can then be generated from the data and a label associated with each curve. These curves can then be used directly for classification purposes or be processed further and then used for classification purposes (further processing might result in a more effective and/or efficient representation). In the first case classification can be conducted simply be comparing new curves associated with unlabelled VOI with existing curves in our "curve base". The proposed process is described in sub-section 3.1 below. In the second case we translate the point series into a standard feature space representation compatible with many "off-the-shelf" classifier generators. This process is described in sub-section 3.2 below.

3.1 Direct Classification

Using the generated point series (curves) directly to classify "unseen" data the use of k-Nearest Neighbours (kNN) classification [3] is proposed with k set to 1. The kNN classification approach requires a distance measure, Euclidean distance is frequently used for this purpose, however this is clearly unsuitable when comparing curves (which may also be of different length). Instead Dynamic Time Warping (DTW) as described in [1] was used to identify a *warping path*. DTW is a well established technique used to compare curves. DTW operates as follows. Given two curves, X with length m and Y with length n, a matrix A is constructed with m rows and n columns. Each element (i, j) within matrix A describes the distance between point i on curve X and the point j on curve Y. The goal is to find the "warping path" through this matrix describing the shortest distance from $(0,0)$ to (m,n). To improve the efficiency with which this warping path can be identified the "Sakoe-Chiba" band [9] was used to define a "constraint region". The length of the warping path can then be used as a measure of the similarity between two curves. Using this approach the most similar curve in the curve based to a given new curve (representing a previously unseen ventricle extracted from a MRI brain scan) can be identified and the label from the identified curve used to label the new curve.

3.2 Classification after Further Processing

The idea behind the further processing of the point series data is that this might result in a more effective representation for classification purposes in that redundant information may be removed. More specifically to idea is to generate a collection of point series using a pre-labelled training set and then converting these point series into a set of "feature vectors" or "signatures" representing key elements of the point series. Collectively the feature vectors (signatures) describe a multi-dimensional feature space (one dimension per feature where each feature has a number of potential values associated with it) in which each point series is described by a single location within the space described by the vector from the origin of the feature space to the location. To this end Hough feature extraction, based on the Hough concept [6], was used to identify signatures from within the point series (curve) data. The curves were firstly transformed into a parameter space (accumulator matrix) A comprised of m rows and n columns where m is *** SAY WHAT m IS —— ——- —— —— —— ——- —— —— —— ——- —— ——*** and n *** SAY WHAT n IS —— ——- —— —— —— ——- —— —— —— ——- —— ——***. The process, based on the Hough transform, described in [11] was then used to extract signatures (feature vectors) from the accumulator matrix. Feature vector representations are compatible with many standard forms of classifier generator. With respect to the evaluation described in the following section a SVM classification model [2] was used.

4 Evaluation

From the foregoing two point series representation methods are proposed (Disc-based and Spoke-based) which can be either used directly for classification purposes (using kNN coupled with DTW in our case) or processed further and then used for classification purposes (using Hough signature extraction and the SVM classification model in our case). The comparative evaluation of these four different mechanisms is presented in this section. For the evaluation a dataset comprised of 210 MRI brain scans, obtained from the Magnetic Resonance and Image Analysis Research Centre at the University of Liverpool, was used. Each scan consisted of 256 two dimensional (2-D) parallel image slices in each of the three cardinal planes. The resolution of each image slice was 256 x 256 pixels (voxels) with colour defined using 8-bit gray scale (256 colours). The data set is described in more detail in [10]. It should also be noted that it has been used in a number of other studies, for example in [4] it was used to determine the relationship between the size of the corpus callosum (another readily identifiable object in MRI brain scan data) and epilepsy, although in this case the study was conducted in 2D using only the mid-sagittal slice of the collected data.

The reported experiments were conducted using Ten-fold Crossed Validation (TCV) where different tenths of the data were used as the test set. In the case of the Spoke-based technique a sequence of values for x were used $\{1°, 2°, 3°, 4°\}$. The SVM model provided with The Waikato Environment Knowledge Analysis (WEKA) data mining workbench [5] was used where required. The classification results obtained are shown in Tables 1 and 2. Table 1 shows the results obtained using direct classification (kNN and DTW similarity measurement) and Table 2 the results after further processing (Hough signature extraction and SVM). Both tables list the accuracy (Accu.), sensitivity (Sens.) and specificity (Spec.) values obtained. From the tables it can be observed that: (i) the spoke based representation outperformed the disc based representation, (ii) the spoke based representation tended to improved as the value of x increased and then drop off (using direct classification $x = 2°$ tended to produced the best results, while with further processing $x = 3°$ tended to produced the best results) and (iii) direct classification produced better overall average results than obtained after further processing. The reason for the Spoke-based representation outperforming the disc based representation is conjectured to be because the spoke based representation was more succinct and therefore less cluttered (less room for ambiguity). The conjectured reason for the direct classification approach outperforming the alternative approach is that the additional processing conducted in the later case had the effect of coarsening the representation with the result that some information was lost. The best accuracy, sensitivity and specificity values were all obtained using the Spoke-based representation and direction calcification: 69.81 ($x = 2°$), 75.47 ($x = 3°$) and 67.92 ($x = 2°$) respectively. It should also be noted that the Spoke based techniques was also more efficient because the resulting point series encompassed fewer points.

Technique	Accu.	Sens.	Spec.
Disc	62.20	67.50	57.14
Spoke ($x = 1°$)	64.15	66.04	62.26
Spoke ($x = 2°$)	69.81	71.70	67.92
Spoke ($x = 3°$)	68.87	75.47	62.26
Spoke ($x = 4°$)	60.98	67.50	57.14
Average	65.20	69.64	61.34

Table 1: Classification results obtained using KNN and DTW

Technique	Accu.	Sens.	Spec.
Disc	59.43	58.49	60.38
Spoke ($x = 1°$)	59.43	58.49	60.38
Spoke ($x = 2°$)	62.20	67.50	57.14
Spoke ($x = 3°$)	64.63	70.00	59.52
Spoke ($x = 4°$)	61.32	62.26	60.38
Average	61.40	63.35	59.56

Table 2: Classification results obtained using Hough Signature Extraction and SVM

5 Conclusions

This paper has proposed an approach to 3-D MRI brain scan classification using two point-series based representations, Disc-based and Spoke-based. These can be used directly (a kNN based approach is suggested) or processed further (a Hough signature extraction approach is suggested) and then input to a standard classifier generation model (the SVM model was used with respect to the reported evaluation). The approaches were evaluated in the context of epilepsy classification with respect to lateral ventricle data obtained from 3-D MRI brain scans. The main findings were that the Spoke-based representation outperformed the Disc-based representation (especially when $x = 2^\circ$ or $x = 3^\circ$) and that direct classification produced better results than when further processing was applied to the point series data. Compare to other previous works the results reported in [4] were slightly better than those reported here, although this work was directed at the corpus callosum which might be a better indicator of epilepsy. Better results were also reported in [8], using an oct-tree representation of the ventricles, although in this case the work was directed at classifying Alzheimer's disease and level of education rather than epilepsy.

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