

Usage of Relevance Vector Machines in Magnetic Resonance Images Segmentation

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ABSTRACT

The aim of this paper is to identify and show that the Magnetic Resonance image classification of brain tissues can be performed better through Relevance Vector Machines. Also Support Vector Machines are used for the arrangement of the tissues of brain as of the effective outcomes exposed in several decoration recognition system and usage of Kernel functions which consequences in extraordinary simplification capability. Magnetic Resonance images are critical for the credentials of humanoid brain infections. Relevance Vector Machines is another form of the Support Vector Machines. Relevance Vector Machines resolves these complications by consuming Bayesian methodology which familiarizes a prior by the set of overexcited constraints on the masses involved with a 1-to-1 communication whose prospect is projected iteratively from data. There are many harmful brain diseases in human i.e. neurodegenerative disorders such as Alzheimer disease, movements disorders such as Parkinson or Parkinson related syndrome, white matter metabolic or inflammatory disease, congenital brain malformations or perinatal brain damage and post traumatic syndrome. MR imaging is an important procedure for the identification of the human brain diseases. MR image segmentation has been used for many diagnosing purposes but automatic segmentation of MR scans is of significant value in research and clinical study of neurological pathology. The correct segmentation of the MR images into various tissues group e.g. gray matter (GM), white matter (WM) and cerebrospinal fluid (CSF) is helpful in diagnosis of many brain diseases. The work described has implemented the classification of the brain tissues in the MR image into four classes i.e. GM, WM, CSF and background with each one has been assigned a different class label. The data for the research is taken from the McConnell Brain Image Centre, Montreal Neurological Institute, McGill University. The total number of values in the data is 39,277. The experimentation has been performed on the data by selecting 200 random values for training, 200 for testing and 200 for predictions.

KEYWORDS: Relevance Vector Machines (RVM), Magnetic Resonance image, (MRI), Relevance Vector Classification (RVC), Human Brain, Neural Network, Kernel Functions.

1. INTRODUCTION

Computer base solutions given by driving, output from a set of inputs which are known explicitly? The system designer and programmer translate such method into a program [1]. But sometimes known method for computing output from input is very expensive e.g. modeling a complex chemical reaction, where exact interaction of the different reactants are not known or classification of protein types based on the DNA sequence from which they are generated or the classification of credit applications into those who will default and those who will repay the loan. Traditional programming cannot give solution for such problems because the systems designers can not accurately indicate a method by which the correct output can be computed from the input data. Another technique is to learn input/output functionality from examples. It is the same way children learn about sports car simply by being told which out of a large number of cars are sporty rather than by being given accurate specification of sportiness. The approach of using examples to produce programs is known as the learning methodology [1]; when examples are input/output pairs than it is called supervised learning. Examples of input/output functionality are known as the training data. The input/output pairing shows functional relationships mapping inputs to outputs. Though not always, as for example data can be corrupted by noise. When there exists a function for mapping input into output than it is called target function. The estimate of the target function which is learned is known as solution of the learning problem. Such functions are known as decision function in classification, where solution is chosen from a set of candidate functions which to do mapping of input to output. Usually a set or class of candidate functions which are called hypothesis before trying to learn the correct function e.g. decision trees are hypothesis which are made by constructing a binary tree with simple decision functions at the internal nodes and outputs values at the leaves. Hypothesis space is

one of the most important elements of the learning strategy [1]. Second important element is the algorithm which takes the training data as input and select a hypothesis from the hypothesis space which is known as learning algorithms e.g. distinguishing sports cars output is simple Yes/No tag, a binary output, while recognizing the protein types will be one of a finite number of categories, output modeling, a chemical reaction will be concentration of reactants having real values. The first one if binary classification problem second is multiclass classification and last one is the regression.

2. MATERIALS AND METHODS

In Relevance Vector Classification (RVC) the class probability of class membership is expected specified the input X [2]. The linear model is widespread by applying logistic sigmoid function [3].

$$\sigma(y) = 1 / (1 + e^{-y}) \text{ to } \mathbf{y}(\mathbf{x})$$

$$P(t | w) = \prod_{n=1}^N \sigma\{y(x_n)\}^{t_n} [1 - \sigma\{y(x_n)\}]^{1-t_n} \quad (1)$$

The RVM classifiers need precise information to be given as input. The image is provided with a detail of features which is required for the high quality of the classification. Textures [4] are used for MR images segmentation which is calculated from overlapping sliding squares windows of the image and represented by central pixel of the window. Another theory is of co-occurrence matrix which identifies and differentiates among various type of texture [5]. In the research eleven textures are used which are as follows.

i. Angular second moment

$$f_1 = \sum_i \sum_j \{P(i, j)\}^2 \quad (5)$$

Contrast

$$f_2 = \sum_i \sum_j (i - j)^2 P(i, j) \quad (6)$$

Correlation

$$f_3 = \frac{\sum_i \sum_j (ij)P(i, j) - \mu_x \mu_y}{\sigma_x \sigma_y} \quad (2)$$

Where $\mu_x, \mu_y, \sigma_x, \sigma_y$ are the means and standard deviation of $p_x(i)$ ($p_x(i) = \sum_{j=1}^{N_g} p(i, j)$) and

$p_y(j)$ ($p_y(j) = \sum_{i=1}^{N_g} p(i, j)$). $p_x(i)$ ($p_y(j)$) is i-th (j-th) entry in the marginal-probability matrix obtained by summing the rows (columns) of $p(i, j)$, and N_g is number of distinct grey levels in image.

ii. Variance

$$f_4 = \sum_i \sum_j (ij - \mu)^2 P(i, j) \quad (3)$$

iii. Inverse difference moment

$$f_5 = \sum_i \sum_j \frac{1}{1 + (i - j)^2} P(i, j) \quad (4)$$

iv. Sum average

$$f_6 = \sum_{i=2}^{2N_g} ip_{x+y}(i) \tag{5}$$

v. Sum variance

$$f_7 = \sum_{i=2}^{2N_g} (i - f_6)^2 P_{x+y}(i) \tag{6}$$

vi. Sum entropy

$$f_8 = -\sum_{i=2}^{2N_g} p_{x+y}(i) \log(p_{x+y}(i)) \tag{7}$$

vii. Entropy

$$f_9 = -\sum_i \sum_j p(i, j) \log(p(i, j)) \tag{8}$$

viii. Difference Variance

$$f_{10} = \sum_{i=0}^{N_g-1} (i - f_{11})^2 p_{x-y}(i) \tag{9}$$

ix. Difference entropy

$$f_{11} = -\sum_{i=0}^{n_g-1} p_{x-y}(i) \log(p_{x-y}(i)) \tag{10}$$

2.1 Kernel Functions

Kernel functions helps in performing operations in the input space rather than potentially high dimensional feature space [6]. The inner product is not needed to be evaluated in the feature space which provides a way of addressing the curse of dimensionality. Computation depends upon the number of training patterns and to provide a good data distribution for high dimensional problem we generally require a large training set.

An inner product in feature space has an equivalent kernel in input space

$$K(x, x') = \langle \phi(x), \phi(x') \rangle, \tag{11}$$

If K is symmetric positive definite function which satisfies mercer's conditions

$$K(x, x') = \sum_m^{\infty} a_m \phi_m(x) \phi_m(x'), a_m \geq 0, \tag{12}$$

$$\iint K(x, x') g(x) g(x') dx dx' > 0, g \in L_2 \tag{13}$$

Then the kernel represents a legitimate inner product in feature space valid functions that satisfy Mercer's conditions are now given, which unless stated are valid for all the real x and x'.

2.2 Neural Networks Approach

Artificial neural networks are used for pattern recognition due to its parallel processing and non-linear properties [7]. It is a composite set of interdependencies, helpful for designing models of any scale of non-linearity which in turn gives very general models because it is made of many computational elements highly interconnected with variably waited links. It searches competing hypothesis simultaneously instead of a sequential program. It is very useful for classification where training time is long. There are many approaches for ANA, some of them are:

2.2a Hopfield Neural Networks (HNN)

It is used for image segmentation on gray level images to reduce appropriate energy function from which network architecture is derived [8]. This method is also extended to color images [9]. This technique is used by unsupervised algorithm for segmentation of liver tissue images. But this technique can divide the nuclei region and cytoplasm region which is useful for diagnosis. It is also used for image segmentation in developing diagnosis system for lung cancer [10]. HNN in this case divide the image into background, cytoplasm and nucleus which have shown useful results but improvements are needed for the case of overlapping cells.

2.2b Self-Organizing Map (SOM)

The SOM project is used for envisioning and investigating characteristics of the data [11]. Self-organization of kohonen feature map (SOFM) is used for data clustering, which solves our segmentation problem. It is useful for quantization of the image for reducing computational time and obtaining indexed image. Local histogram and indexed-count vectors are acquired which is used for training data for SOFM. In the end indexed-count space is mapped to the original image.

2.3c Other Neural Networks

Back propagation (BP) algorithm, C-mean and Learning Vector Quantization (LVQ) are also used for image segmentation [12]. Local linear map network (LLM) [13] is based on self-organizing map which is feed forward neural networks; it is trained in supervised learning method and used for image segmentation [13]. The Oscillatory cellular neural network (OCNN) [14] is also used for color image segmentations; its major advantage is that it reduces the problem which arises from the large number of connections between a global separator and oscillators [15].

3. RESULTS AND DISCUSSIONS

The increase of the research in the field of computer based quantitative analysis of medical image data has increased the requirement of the validation of these techniques [16]. These techniques are not easy but Simulated Brain Database (SBD) provides a solution to the validation problem [16]. It consists of realistic MRI data sets developed from through an MRI simulator [16]. This data is used by neuroimaging researcher for the evaluation of different image analysis techniques.

The SBD is based on the two anatomical models [16]; these are Normal and Multiple sclerosis (MS)

These techniques are based on the three dimensional data volumes with three sequences (T1-, T2-, and proton-density-(PD-) weighted), a mixture of slice thickness, noise levels and levels of non-uniformity [16].

This data is offered in three orthogonal views which are as follows:

- Transversal
- Sagittal
- Coronal

There are two types of SBD [16].

1. Normal Brain database
2. MS Lesion Brain Database

The Magnetic Resonance Image of the brain is shared into four fragments the three kinds of brain tissues identified as CSF, WM, GM and background [17].

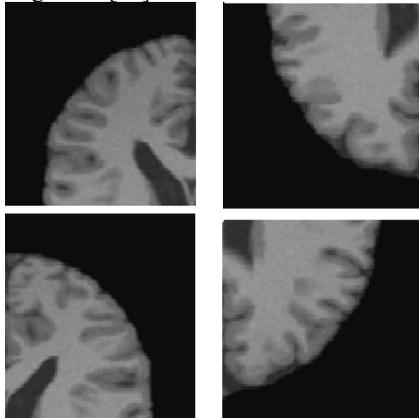


Fig: Magnetic Resonance Image of Human brain [17]

1 Anatomical Model of Normal Brain

This model is developed from the simulated brain MRI data consist of three dimensional fuzzy tissue, each belonging to one of the CSF, GM, WM, FAT, Muscle/Skin, Skin, Skull, Glial matter and connective [18]. The voxel values in this volume of data shows the proportion of tissues present in that voxel in range [0, 1] [18]. The volumes are defined at a 1mm isotropic voxel grid in Talairach space, with dimensions 181x217x181 (XxYxZ) and start coordinates -90, -126, -72 (x, y, z) [18]. The discrete anatomical model has also class labels (0=Background, 1=CSF, 2=Grey Matter, 3=White Matter, 4=Fat, 5=Muscle/Skin, 6=Skin, 7=Skull, 8=Glial Matter, 9=Connective) [18]. The data in parenthesis shows the volume in cubic mm for each tissue class in the model [18]. This Fuzzy model contains the following tissues:

Background (3001960)

The images below are used to produce the required image signal from the selected tissue class for the MR simulator [18].

Phantom, fuzzy, background

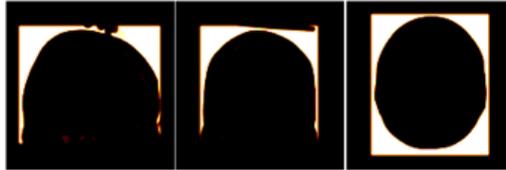


Fig 2: Background Image of the Brain [18]

CSF (371945)

The images below are used to produce the required image signal from the selected tissue class for the MR simulator [18].

Phantom, fuzzy, CSF

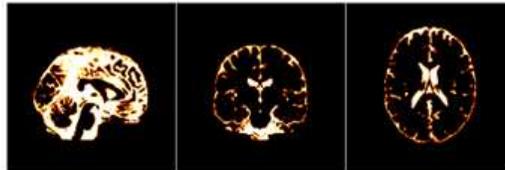


Fig 3: CSF Image [18]

Grey Matter (902912)

The images below are used to produce the required image signal from the selected tissue class for the MR simulator [18].

Phantom, fuzzy, grey matter

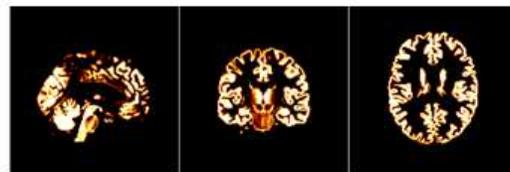


Fig 4: Grey Matter Image [18]

White Matter (674777)

The images below are used to produce the required image signal from the selected tissue class for the MR simulator [18].

Phantom, fuzzy, white matter

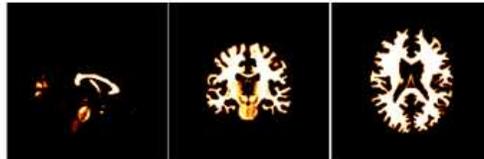


Fig 5: White Matter Image [18]

Fat (146514)

The images below are used to produce the required image signal from the selected tissue class for the MR simulator [18].

Phantom, fuzzy, fat

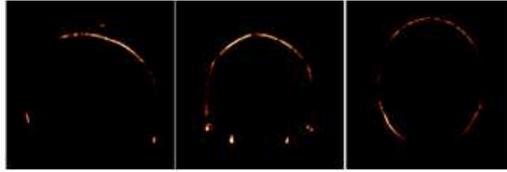


Fig 6: Fat Image Anatomical Model of Normal Brain, 2008

Muscle / Skin (617482)

The images below are used to produce the required image signal from the selected tissue class for the MR simulator [18].

Phantom, fuzzy, muscle / skin



Fig 7: Muscle/Skin Image Anatomical Model of Normal Brain, 2008

Skin (726649)

The images below are used to produce the required image signal from the selected tissue class for the MR simulator [18].

Phantom, fuzzy, skin

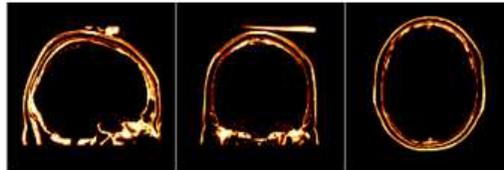


Fig 8: Skin Image [18]

Skull (362561)

The images below are used to produce the required image signal from the selected tissue class for the MR simulator [18].

Phantom, fuzzy, skull



Fig 9: Skull Image [18]

Glia Matter (5987)

The images below are used to produce the required image signal from the selected tissue class for the MR simulator [18].

Phantom, fuzzy, glial matter



Fig 10: Glial Matter Image [18]

Connective (298350)

The images below are used to produce the required image signal from the selected tissue class for the MR simulator [18].

Phantom, fuzzy, connective

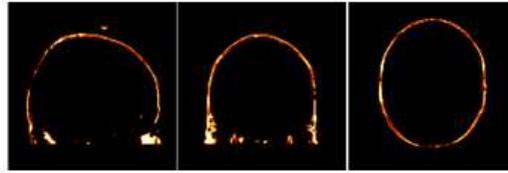


Fig 11: Connective [18]

Implementation

The scaling of data has been performed through LIBSVM. The scaling is then followed by actual implementation. In implementation the data was supposed to be divided into three parts, which is:

- Training data
- Test data
- Prediction

The brain tissues MR images data is divided into three parts, so that the supervised learning methodology can be applied properly. The supervised learning is based on learning from examples, so to accomplish this first 200 sample data from the scaled format would be taken and then tested against the trained data. The third portion was to be used for the predictions [19]. The classification of the three brain tissues (WM, GM, and CSF) and the background is performed on the basis of assigning a different class label to each of them. There are large numbers of background pixels as compared to the brain tissues so to avoid this problem such samples are taken which can equally represent all the pixels [20].

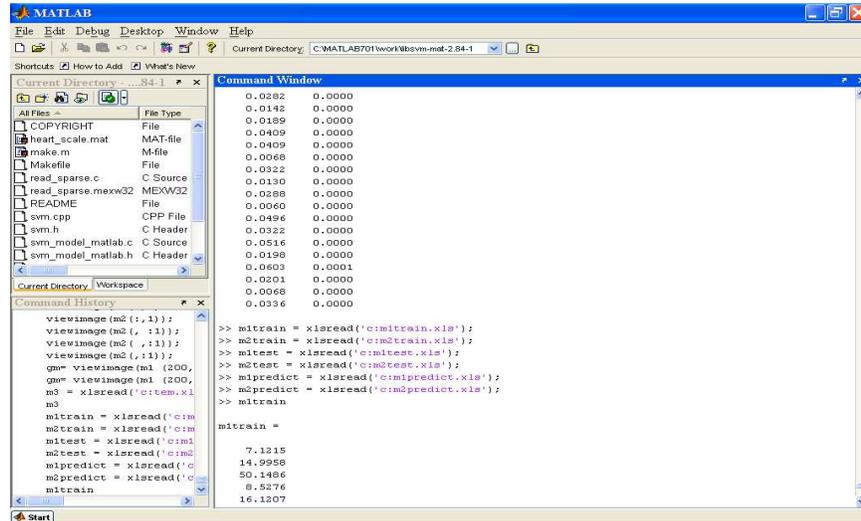


Fig 12

The fig 12 shows the command for importing the data from Excel to MATLAB. Xlsread function is used for importing data from an Excel spreadsheet file into MATLAB. The reason for using the Excel spreadsheet is to make the process of random selection of data easy. This randomly selected data is divided into three parts training, testing and prediction. The variable m1train is x-coordinate of the data i.e. input while m2train represents the corresponding labels. Similarly, variables m1test, m2test, m1predict and m2predict represent the corresponding input and labels for testing and prediction [21,22].

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