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Sequential Minimal Optimization Approach for Content Based Image Retrieval

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Abstract

Content Based Image Retrieval (CBIR) is an emerging method to search and access images using either an image or the image dependent information as the query. Content-based image retrieval has huge advantage in medical field to provide doctors with a powerful tool to make accurate diagnosis. For CBIR to be effective, the system should be capable of retrieving images from the same disease class as the patient. In this paper we investigate the extraction of histogram from an image and use the Sequential minimal optimization technique to classify images via resampling.

Index Terms: CBIR, histogram, SMO, Data mining, Image processing, Image classification.

Introduction
Content based image retrieval (CBIR) systems are based on the description of image features such as colors, gray shade, texture, contours, shapes . A retrieval algorithm matches these descriptors and based on similarity metric retrieves relevant images[1],[2]. The effectiveness of a CBIR system depends on the choice of the set of visual features and on the choice of the metric that models the user's perception of similarity. In the last couple of years several useful research prototypes in the medical domain have been successfully implemented with each work catering to specific areas[3],[4].

A hospital can generate thousands of diverse images of different modalities everyday. Retrieval from these heterogeneous images is much more complex as compared to a single image modality. Complexity arises when different modalities contain images of the same body part and visual appearances are quite similar except for few subtle anatomical or physiological differences. For example, a patient with a brain disease may undergo several diagnostic tests and the image acquisition devices may capture MRI and PET images of the brain for an efficient diagnosis. Here, the variation of visual attributes is very subtle between these two images and can be judged only by experts related to that field. Thus, in traditional CBIR, a query with an MRI image may retrieve some PET images too, although those are not expected by the user[5].

In this paper we extract the histogram from the given medical images, resample the images and apply Sequential minimal optimization classification techniques to classify the images accordingly.

This paper is organized into the following sections. Section II deals with the methodology used, section III deals with the dataset and section IV deals with the analysis and results.

Proposed methodology

The block diagram of the proposed methodology is illustrated in figure 1. The Histogram shows the total tonal distribution in the image. It's a barchart of the **count** of pixels of every tone of gray that occurs in the image. Every pixel in the Color or Gray image computes to a Luminance value between 0 and 255. The Histogram graphs the pixel count of every possible value of Luminance, or brightness if it helps to think of it that way[6]. Luminance is brightness the same way the human eye sees it, as opposed to absolute brightness. Anyway, the total tonal range of a pixel's 8 bit tone value is 0..255, where 0 is the blackest black at the left end, and 255 is the whitest white at the right end. The height of each vertical bar in the histogram simply shows how many image pixels have luminance value of 0, and how many pixels have luminance value 1, and 2, and 3, etc, all the way to 255 at the right end. For this research we used labview to extract the pixel values for the images in the database[7].

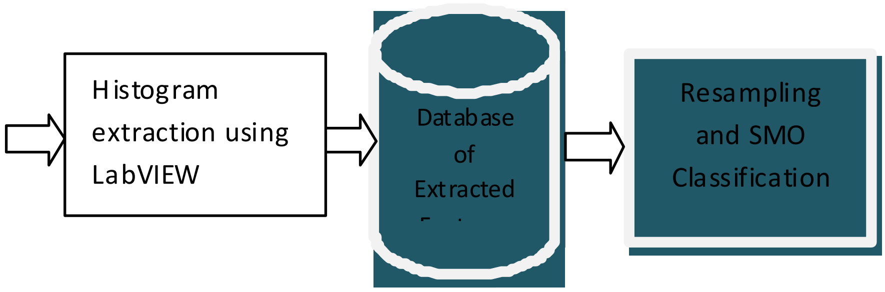

Figure1: Proposed block diagram.

Resampling is the estimation of the precision of sample statistics including medians, variances and percentiles by typically using subsets of available data.

Support vector machines (SVMs) is a supervised learning methods used in classification and regression analysis. An SVM training algorithm builds a model that can classify whether a new sample falls into which of the category the system is trained for. An SVM model is a represented by drawing an hyperplane or a set of hyperplanes which broadly divides the category into two sets. SVM states, a good separation is achieved by the hyperplane that has the largest distance to the nearest training datapoints of the class, as the larger the margin the lower the generalization error of the classifier.

Training a support vector machine requires the solution of a very large quadratic programming (QP) optimization problem. SMO breaks this large QP problem into a series of smallest possible QP problems[8]. The smaller QP problems are avoids time consuming QP optimization during analysis. During training the memory size is linear with respect to the data and hence SMO can handle large training sets.Since matrix computation is avoided, SMO scales somewhere between quadratic and linear in the training set size for various test problems, while the standard chunking SVM algorithm scales somewhere between cubic and linear in the training set size. SMO's computation time is dominated by SVM evaluation, hence SMO is fastest for linear SVMs and sparse data sets.

To solve the two Lagrange multipliers, SMO computes the constraints on these multipliers for the constrained minimum.. Without loss of generality, the algorithm first computes the second Lagrange multiplier α2 and computes the ends of the diagonal line segment in terms of α2. Assuming the target *y*1 equals the target *y*2, SMO computes the minimum along the direction of the constraint :

$$\alpha_2^{new} = \alpha_2 + y_2(E_2 - E_1) / \eta$$

where E_i is the error of the i^{th} training example.

Dataset used

A popular source for MRI medical images are scan centres. We approached a popular scan centre and obtained images from the centre. The data so obtained was anonymized to protect the privacy of the patients. This data along with publicly available data was combined to form our data set. Figure 2 shows some of the data used in this work. These images were also used in our previous work[9]. A total of 87 images of 6 different types were used in our work

Experimental Results and analysis

LabView was used to create an application which takes a batch of images as the input and the output is a transposed row of the histogram intensities. Since we used 8 bit gray scale images the output contained 256 columns. Class labels were assigned based on the type of image for the training set. Screen shots of our an image converted is shown in figure 3 and figure 4.

Figure3: An image for which histogram is to be measured.

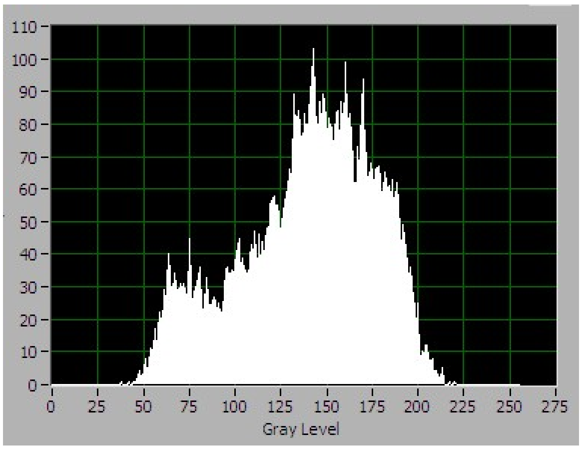

Figure4: The histogram of image in figure 3.

A total of 87 images were used in the database and for all this 87 images, it corresponding histogram was created. The data so created was converted into arff format popularly used by the WEKA data mining software. Resampling was applied and SMO classification techniques was applied. The result generated is shown in table 1.

Table1: Classification with various % of training set.

	Correctly Classified Instances
60% Training set	68.5714
70% Training set	76.9231
80% Training set	82.3529

SMO is able to classify medical images in the range of 69.77 to 82.35% accuracy. Higher training set has established better results. Histogram as a feature set alone has given good results. Combination of histogram with some other features in the image can improve the results and needs to be investigated.

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