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TEXTURE FEATURE EXTRACTION AND CLASSIFICATION USING RADIAL BASIS FUNCTION FOR DIAGNOSIS OF BRAIN TUMOUR

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Abstract

Texture features are playing major role now-a-days for the analysis of medical images. With the help of texture features extraction and classification, we can differentiate between pathological and healthy issues in various organs. In this paper, we have formed gray level co-occurrence matrix (GLCM) for MR brain images. Then, we have extracted Haralick texture features and then used support vector machine (SVM) using Gaussian radical basis function for classification between malignant and healthy brain. The performance of various texture features are compared in terms of percentage accuracy for the correct classification of images.

I. Introduction

The use of radiological images for the diagnosis of diseases is increasing day by day. Due to large number of patients, it is becoming very hard for medical practitioners to investigate all images in the specified time. To solve the problem, attempts were made to use computer aided techniques to

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investigate the medical images.

The texture of an image refers to the underlying appearance, structure and arrangements of various parts of the object in the image [1]. Texture analysis aims in finding a unique way of representing the characteristics of textures and to represent them in some mathematical form, so that they can be used for robust, accurate classification and segmentation of objects [2]. Analyzing a texture is a complicated process because of the variations in the periodicity, directionality and randomness of the image [3].

Texture analysis has been done using statistical approach using calculation of gray level histogram [4]. They provide details about the spatial distribution of pixels in an image. In recent years, several important advancements have been made in the field of texture analysis [5-8].

The remaining of this paper is organized as follows: Section 2 explains about Gray Level Co-occurrence Matrix (GLCM), and texture feature extraction using Haralick methods [9]. Section 3 explains about the proposed method, Section 4 discusses about results and comparative analysis of features, conclusion is given in Section 5, finally future scope of the improvement is given is Section 6.

2. Gray Level Co-occurrence Matrix

The gray level co-occurrence matrix (GLCM) proposed by Haralick et al. [9], is a matrix that contains the spatial distribution of pixels having similar gray level values. GLCM extracts the structural information about the texture pattern which are analysed at different scale and orientation. The procedure makes the GLCM more effective but at the cost of increased computational efforts. GLCM provides a mapping about how different combinations of pixel intensity pairs occur in an image. A co-occurrence matrix is given as follows [10]:

$$P_d = \| \{((a1, b1), (a2, b2)) : I(a1, b1) = r, I(a2, b2) = s\} \|,$$

where P_d is the matrix which measures the spatial dependency of two gray levels, *r* and *s* are the displayment and *d* is the distance.

We use ten textural features in our proposed work. Following are the equations defining these features. Let $p(i, j)$ be the (i, j)th entry in a normalized GLCM. The mean and standard deviations for the rows and columns of the matrix are:

$$\mu_x = \sum_i \sum_j i \cdot p(i, j), \quad \mu_y = \sum_i \sum_j j \cdot p(i, j)$$

$$\sigma_x = \sum_i \sum_j (i - \mu_x)^2 \cdot p(i, j),$$

$$\sigma_y = \sum_i \sum_j (j - \mu_y)^2 \cdot p(i, j).$$

The features are as follows:

1. Autocorrelation [11]:

$$f_1 = \sum_i \sum_j (i, j)\, p(i, j).$$

2. Contrast [10]:

$$f_2 = \sum_i \sum_j (i - j)^2\, p(i, j).$$

3. Correlation [11]:

$$f_3 = \frac{\sum_i \sum_j (i, j)\, p(i, j) - \mu_x \mu_y}{\sigma_x \sigma_y}.$$

4. Cluster Prominence [11]:

$$f_4 = \sum_i \sum_j (i + j - \mu_x - \mu_y)^4 \cdot p(i, j).$$

5. Cluster Shade [11]:

$$f_5 = \sum_i \sum_j (i + j - \mu_x - \mu_y)^3 \cdot p(i, j).$$

6. Dissimilarity [11]:

$$f_6 = \sum_i \sum_j |i - j| \cdot p(i, j).$$

7. Energy [11]:

$$f_7 = \sum_i \sum_j p(i, j)^2.$$

8. Entropy [11]:

$$f_8 = -\sum_i \sum_j p(i, j) \log(p(i, j)).$$

9. Homogeneity [11]:

$$f_9 = \sum_i \sum_j \frac{1}{1 + (i - j)^2} p(i, j).$$

10. Maximum Probability [11]:

$$f_{10} = \max_{i, j} p(i, j).$$

3. Proposed Work

We have taken the database of 50 MR brain images obtained from NIMS Medical College & Hospital, Jaipur, India. The database is then divided into 30 images comprising training set and 20 testing images comprising testing set. Both sets contain malignant and healthy brain MR images. Then, we have extracted the above mentioned ten texture GLCM features for both the training set and testing set. The results are stored in the form of tables and used further for classification in which we have used the support vector machine (SVM) using Gaussian radical basis function. The results are further stored and then a comparative analysis of various texture features is given in terms of percentage accuracy of various above mentioned features.

The whole procedure can be understood with the help of the following flow chart:

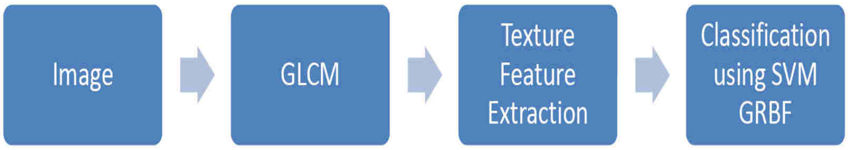

Figure 1. Flow chart of the proposed work.

4. Results and Discussions

The following table shows the result of various texture features for ten images from testing set for malignant brain MR images.

Table 1. Texture features extracted for ten images from testing set for malignant images

Image Name	Auto-correlation	Contrast	Correlation	Cluster Prominence	Cluster Shade	Dissimilarity	Energy	Entropy	Homogeneity	Maximum probability
61.jpg	9.451	2.074	0.745	754.218	63.149	0.608	0.243	2.433	0.808	0.474
62.jpg	8.503	2.058	0.718	647.518	55.254	0.594	0.254	2.349	0.814	0.483
63.jpg	9.333	0.990	0.838	315.886	22.361	0.331	0.259	2.077	0.884	0.440
64.jpg	9.269	0.999	0.838	328.747	23.885	0.336	0.263	2.067	0.882	0.447
65.jpg	9.303	0.919	0.851	334.129	24.775	0.324	0.261	2.103	0.883	0.452
66.jpg	10.577	0.952	0.866	362.636	24.418	0.334	0.245	2.186	0.880	0.448
67.jpg	10.791	1.886	0.745	476.679	31.942	0.596	0.184	2.593	0.803	0.371
68.jpg	7.912	0.871	0.834	279.079	23.442	0.278	0.290	1.893	0.904	0.480
69.jpg	10.630	1.870	0.717	344.576	17.012	0.572	0.206	2.413	0.815	0.354
70.jpg	7.106	1.681	0.610	213.923	16.936	0.534	0.214	2.299	0.822	0.341

The programming language used for the proposed work is MATLAB. The Haralick et al. [9] texture features are programed using the above equations and then the features are extracted for training set and testing set and then classification is done using support vector machine using Gaussian radical basis function. These classification results are also stored in the form of tables for various features. Then a comparative analysis of various features is presented in terms of percentage accuracy of classification of healthy brain images among malignant brain images.

The whole procedure is repeated for two data sets. The result of comparative analysis for the two datasets is shown in Table 2:

Table 2. Comparative analysis of various texture features for the classification of brain MR images

Feature Name	Classification Percentage Accuracy for Data Set 1	Classification Percentage Accuracy for Data Set 2
Autocorrelation	10	27
Contrast	15	40
Correlation	30	50
Cluster Prominence	35	27
Cluster Shade	40	33
Dissimilarity	15	37
Energy	65	60
Entropy	25	47
Homogeneity	25	33
Maximum Probability	60	67

The above result is shown below in the form of graphical representation.

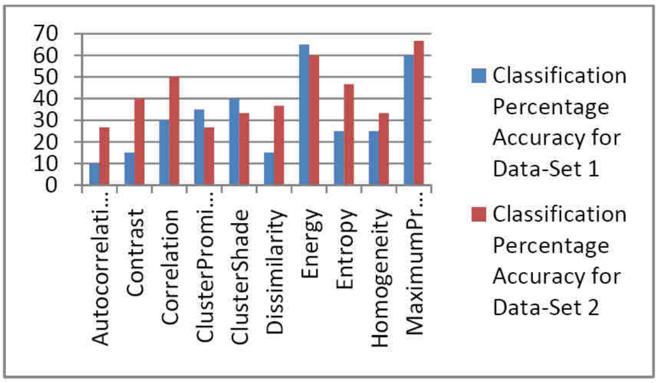

Figure 2. Graphical representation of the comparative analysis of various texture features for the classification of brain MR images.

From the result, it can be seen that in both the data-sets, the two effective features for the classification purpose which are giving the maximum result are Energy and Maximum Probability.

5. Conclusions

The paper presents a comparative analysis of various texture features. The texture features are extracted first by forming Gray Level Co-occurrence Matrix (GLCM) and then implementing various feature equations for calculation. Finally the classification of healthy brain MR images among malignant images has been done with the help of support vector machine (SVM) using Gaussian radical basis function.

6. Future Work

Our future plan is to improve the classification accuracy by using some preprocessing in image database. The other remaining texture features like Variance, Inverse of Difference Moment etc. can also be calculated for improving the classification results. Further texture classification can be done using wavelets packet signatures. Also, soft-computing techniques can be applied for pattern classification and object recognition.

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