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Performance Analysis of Classification of DCE - MRI Using SVM

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Abstract: ***Dynamic contrast enhanced MRI provides insight into the vascular properties of tissue. Pharmacokinetic models may be fitted to DCE-MRI uptake patterns, enabling biologically relevant interpretations. The aim of our study was to determine whether treatment outcome for patients with locally advanced cervical cancer could be predicted from Brix parameters. First order statistical features of the Brix parameters were used. In addition, texture analysis of Brix parameter maps was done by constructing gray level co-occurrence matrix (GLCM) from the maps. Clinical factors such as first and second order features were used as explanatory variables for support vector machine (SVM) classification, with treatment outcome as response. Features derived from first order statistics could not discriminate between cured and relapsed patients. However, second order GLCM features could significantly predict treatment outcome with more accuracies. The result indicates the spatial relation with in tumor, quantified by texture features, were more suitable for outcome prediction than first order features.***

Keywords: Cervix, Magnetic Resonance Imaging (MRI), Features Extraction and Classification

1. Introduction

Magnetic resonance imaging (MRI) is one of the important technique for planning and monitoring cancer treatment. Here, tissue distribution is imaged as a function of space and time [1]. Unlike a conventional MRI [2] which is linked to tumor oxygenation [3]. DCE-MRI is useful tool for prediction of treatment outcome and planning [4].

Brix parameters can be used to capture the properties of a tumor related treatment outcome. Texture analysis is used to capture important characteristics of an image [5], [6]. Texture features can be used for tumor classification [7]. Gray level co-occurrence is one approach for texture analysis, here GLCM is constructed, from which second order statistical features of texture can be calculated [5]. GLCM texture analysis is computationally efficient [10]. GLCM based features from DCE-MRI can also used for different types of cancer [11].

DWT Algorithm is used for features extraction and noise removal from an input image. In past few years DNN is mainly used by many researchers. DWT combined with DNN results to be more accuracy and performance. CNN can be applicable for image recognition, object detection, face recognition, fingerprint pattern classification, etc. Support vector machines (SVM) method is introduced for classification. Support vector machines method is used in many medical imaging applications [13].

The aim of the current study was to identify the patient to be normal or critical stage by using SVM classifier via Brix parameters estimation and GLCM and performance of proposed method to be analyzed. This study shows that the performance is more than previous methods because of features vector based classification.

This paper is organized as follows. Section II includes some notations and preliminaries of proposed method. In Section III, the proposed system and its motivations are introduced. We then develop algorithm for solving the proposed model. Section IV presents some experimental results. Finally, we conclude this paper with some discussions on future research in Section V.

2. Materials and Methods

The data in this study consisted of dynamic contrast enhanced magnetic resonance images patients with cervical cancer. The size of tumor is different for different patient. The tumors are in stage I, stage II, stage III and stage IV. The three-dimensional parameter maps were transformed into two-dimensional images by appending tumor slices. Brix parameters can be used to predict the treatment outcome for a particular patient

The relative signal increase (RSI), in the tumor can be calculated by comparing the signal at time *t* denoted as s(t) to the signal before injection of the contrast agent denoted as s(0). It is represented by,

$$RSI(t) = \frac{S(t)-S(0)}{S(0)} \qquad \text{(II.1)}$$

The pharmacokinetic Brix model can be defined as,

$$RSI(t) = A\frac{k_{ep}}{k_{el}-k_{ep}}\left(e^{-k_{ep}t} - e^{-k_{el}t}\right) \qquad \text{(II.2)}$$

Where, *A* is the amplitude, *kep* is the transfer rate of contrast agent from the tumor tissue to the blood stream and *kel* is the washout rate of contrast agent from the blood plasma.

3. Proposed Method

The proposed system uses a medical image classification using SVM technique. Cervical cancer classification is a two step process,

- Testing
- Training

The testing and training stage consist of,

- Brix Parameters Estimation
- GLCM

Cervical cancer patient images are taken as input to proposed method. In training phase set of images to be trained and in testing particular new sick patient image to be

tested. The input 3D image is transformed into 2D images by Brix parameters maps.

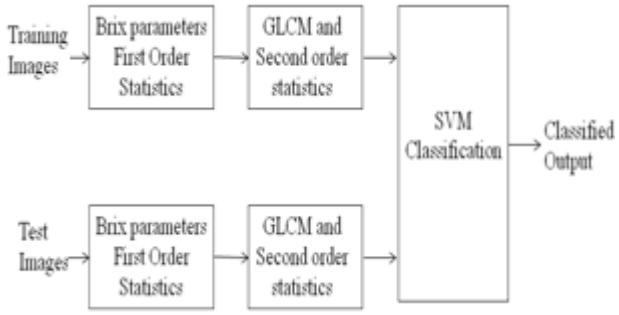

Figure 1: Block diagram of proposed method for SVM Classification

Fig. 1 shows that block diagram of proposed method for cervical cancer image classification using SVM. First features are extracted from training images by Brix parameter estimation and GLCM then image trained and classes to class label. New patient's cancer images are given to test image and features are extracted. Based on features SVM classified as cervical cancer as normal are critical stage.

a) First Order Statistics

Brix parameters can be used to captures the properties of tumor treatment outcome. The mean, median, mode, standard deviation, maximum and minimum value, skewness, and kurtosis of each Brix parameter (*A*, *kep*, and *kel*) were calculated for each tumor. Brix parameters are based on variance. Where A is amplitude, *kep* is transfer rate of contrast agent from tumor to blood and *kel* is washout rate of contrast agent from blood. In addition, percentile values from 10% to 90% with 10% increments, and the percentile widths from 25% to 75% and from 10% to 90% were included to obtain a good representation. Totally, 21 first order statistical features were calculated for each of the three Brix parameters. This can be used to predict treatment outcome for particular patient.

Table I: First Order Statistics Parameters

Sl.No	*First Order Statistics*
1	Mean
2	Median
3	Mode
4	Standard Deviation
5	Maximum Value
6	minimum Value
7	Skewness
8	Amplitude
9	Transfer rate of contrastment
10	Washout rate of contrast agent from blood plasma
11	10% percentile values
12	20% percentile values
13	30% percentile values
14	40% percentile values
15	50% percentile values
16	60% percentile values
17	70% percentile values
18	80% percentile values
19	90% percentile values
20	25% to 75% percentile width
21	10% to 90% percentile width

b) Gray Level Co-occurrence

A Gray Level Co-occurrence Matrix can be constructed by square matrix where the number of rows and columns equals the number of gray levels in the original image. The GLCMs can be obtained by dividing each element with the sum of all elements in the matrix. Before constructing GLCM neighborhood to be choose. Here, 4th neighborhood method is chosen for easiest process. Then normalized GLCM is calculated. In normalized matrix, the sum of all elements to be one.

Second order statistical features can be calculated from the gray level co-occurrence matrix. The four features calculated from GLCM are Contrast, Correlation, Energy, and Homogeneity.

First measures the contrast in gray level from one pixel to its neighbor as defined as,

$$K = \sum_{(i,j)}((i-j)^2 p(i,j)) \qquad \text{(III.1)}$$

Second measures the correlatin between intensities in neighboring pixels as defined as,

$$R = \sum_{(i,j)}\left(\frac{(i-\mu_i)(j-\mu_j)p(i,j)}{\sigma_i \sigma_j}\right) \qquad \text{(III.2)}$$

Third measures the sum of square of all elements in GLCM as defined as Energy. It can be expressed as,

$$E = \sum_{(i,j)}((p(i,j))^2) \qquad \text{(III.3)}$$

Fourth measures the closeness of elements in GLCM to the diagonal as defined as Homogeneity. It can be expressed as,

$$H = \sum_{(i,j)}\left(\frac{p(i,j)}{1+|i-j|}\right) \qquad \text{(III.4)}$$

The four features calculated from the matrix can be used to SVM classification.

c) Classification

Image classification is the process of classifying an image according to features of individual image. Two major steps in an image classification are,

- Features Extraction
- Classification

SVM based on the concept of decision plane that defines the decision boundaries. Supervised image classification can be divided in to two phases such as training data set and testing data set. Which consist of some data instance. Instance in training set consist of one class label and several features. In training phase, features are extracted based on energy, color and edges, etc. After features extraction images can be classified to corresponding image label. In testing phase also features extracted from testing image. After this process, the feature vector of testing image to be compared with feature vector of image label. Once the match is found with any of the class, an image is stored and labeled with same class. Images can be classified to level 1, level 2, level 3 and level 4. Level 1 is labeled as normal stage and level 4 are classified as critical stage.

4. Experimental Results and Discussion

The proposed classification technique is implemented in the working platform of MATLAB with machine configuration. Cervical cancer is a type of cancer that occurs in cells of

cervix (lower part of uterus that connects to vagina). Magnetic Resonance Imaging (MRI) is a medical imaging technique (non-invasive method) that can be used in radiology to generate image of organs in the body. In our proposed method, patient with cervical cancer images are given to an image classification process by using the techniques GLCM and SVM.

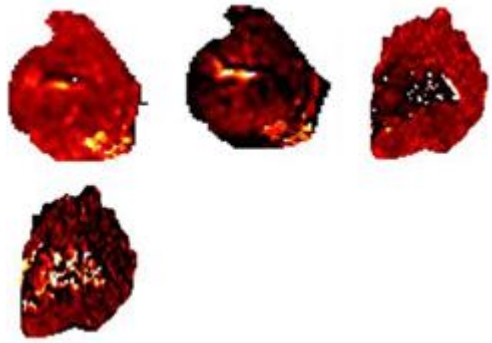

Figure 2: Cervical cancer images with different stages

Fig. 2 shows that, different patient with different stage of cervical cancer. These images are taken as input image of proposed system. From an image features are extracted and based on features images are automatically classified by SVM.

1	2	3
4	5	6
4	3	2

(a)

0	0	0	0	0	0	0
0	0	1	0	1	0	0
0	1	0	2	0	1	1
0	0	2	0	1	1	1
0	1	0	1	2	1	0
0	0	1	1	1	0	1
0	0	1	1	0	1	0

(b)

0	0	0	0	0	0	0
0	0	0.0435	0	0.0435	0	0
0	0.0435	0	0.0870	0	0.0435	0.0435
0	0	0.0870	0	0.0435	0.0435	0.0435
0	0.0435	0	0.0435	0.0870	0.0435	0
0	0	0.0435	0.0435	0.0435	0	0.0435
0	0	0.0435	0.0435	0	0.0435	0

(c)

Figure 3: Image classification based on Second order statistics (a) Example image (b) GLCM matrix (c) Normalized GLCM

Fig. 3 shows that image classification based on second order statistics. For example consider an image (a) that GLCM and normalized GLCM to be shown in (b) and (c) respectively. The sum of all elements in normalized GLCM to be 1. The second order statistics parameters is given by,
Contrast, K = 3.5333 and Correlation, R = Undefined
Energy, E = 0.0300 and Homogeneity, H = 0.3189

Table II: Performance Comparison

Noise level to be added 0.0008		
Parameter	First Order	Second Order
Total Checked	16	16
Correctly Detected	8	12
Incorrectly Detected	8	4
Accuracy	50	75

Table II shows that performance comparison of first order and second order statistics. There may be noise can be added in image capturing process. When noise is added to an image, an accuracy of second order statistics is higher than first order statistics parameters.

In performance analysis we have measured an accuracy using the formula,

$$Accuracy = \frac{total\ number\ of\ images\ correctly\ classified}{total\ number\ of\ images\ tested} x100$$

Accuracy is based on four parameters such as True Positive (TP), False Positive (FP), True Negative (TN) and False Negative (FN).
TP - Sick people correctly identified as sick.
FP - Healthy people incorrectly identified as sick.
TN - Healthy people correctly identified as healthy.
FN - Sick people incorrectly identified as healthy.

Accuracy can be defined as total number of image correctly classified divided by total number of image tested. When the test image suffers from noise, accuracy is more for second order statistics parameters than first order statistics parameters. The high accuracy value is 1(100%) and low value is 0 (0%).

Table III: Performance Analysis

Noise intensity	First order statistics parameters	Second order statistics parameters
0	100	100
0.05	94	98
0.1	86	94
0.15	80	90
0.2	70	84
0.25	64	74
0.3	58	70
0.35	48	62
0.4	44	58
0.45	30	50
0.5	12	38

Table III shows the performance analysis of the proposed system for image classification technique. The performance analysis shows when noise is added to an image, the performance analysis of proposed system with GLCM and without GLCM. When the noise intensity increases, the performance analysis of proposed system with GLCM is best than system without GLCM.

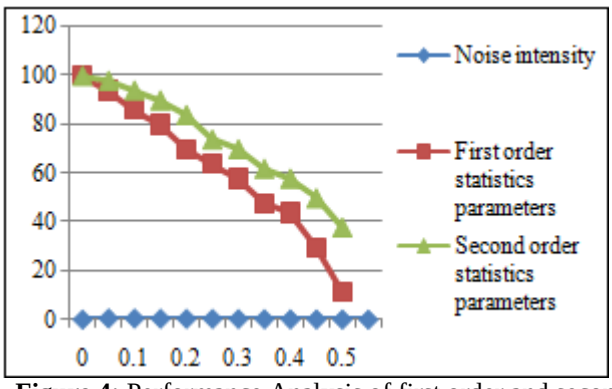

Figure 4: Performance Analysis of first order and second order method

Fig. 4 shows that performance analysis of first order and second order method. In above figure red line denotes first order parameters and green line denotes second order parameters performance. For both methods the performance analysis is low when noise increases. If two methods are combined for features extraction then classification becomes fast and performance and accuracy increases.

From this project work, it can be easily observe that proposed method yield more satisfying results and can applied to different type of images. In future this method can be applied to different medical imaging process and also uses different classification methods to classifying images. The most important application of SVM is to recognize hand-written character.

5. Conclusion

In this paper, we demonstrated that image classification could be modeled with the features extraction. Based on this context, we proposed a GLCM and SVM for classifying cervical cancer images. Features are extracted from images using Brix Parameters Calculation and GLCM methods. Based on features SVM automatically classify patient as normal or critical stage. The Performance analysis of the GLCM shows that more accuracy. The results shows that the complexity of the image classification process reduces highly because the proposed system classifies an image to class label automatically based on vector features. The accuracy of first order and second order statistics parameter method reduces as the noise intensity increases. But the accuracy of second order is more than first order statistics parameter method for the every noise intensity.

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