

Classification of CT liver images using local binary pattern with Legendre moments

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Liver cancer leads to more number of human deaths nowadays. Patient survival chances can be increased by early detection of the tumour. Texture analysis based on moment features for CT liver scan images is proposed here. The texture feature is extracted by local binary pattern and statistical features are extracted by Legendre moments. This communication presents a comparative analysis between these Legendre moments, local binary pattern and combined features. The classification accuracy of 96.17% is obtained for CT liver images. The experimental result shows that better texture classification is obtained using the proposed method.

Keywords: CT liver images, feature extraction, Legendre moments, local binary pattern.

LIVER being a vital organ, liver diseases pose a life threat to human beings. Computer-aided liver diagnosis and analysis is a technique for the automatic detection of tumour, and an alternative tool for radiologists to identify diseases accurately in such a way to reduce liver surgery. The computer-aided liver tissue classification system consists of the segmentation of liver lesion from the database, extraction of features from a lesion, and characterization or classification of liver diseases using a classifier. To improve the performance of CAD systems, various segmentation methods and classifier systems have been proposed by many authors. The classification of liver tissues from abdominal Computed Tomography (CT) images using moments features is the focus of this communication. The various methods are analysed and the results are summarized. The direction for future work is also discussed.

In recent times, computed-aided analysis and processing of medical images is an active research field. The pixel intensities of medical images are not smooth and uniform. However, the images are homogeneous and exhibit patterns. Therefore, texture plays an important role in the processing of these images.

Moments represent global features which are widely used in the application of image processing. Moments features are able to distinguish different types of images. Since Hu¹ proposed image analysis using moments, Tuce-ryan⁴ and Begum⁵ have focused on geometric moments and complex moments for texture feature extraction and

segmentation respectively. The redundant information is available in both geometric and complex moments which are sensitive to noise. To reduce noise, Teague⁶ used orthogonal moments like Zernike moments and Legendre moments in image analysis. Orthogonal moments are shown to be less sensitive to noise and have an efficient capability in feature representation⁴⁻⁶. Orthogonal moments allow the reconstruction of an image intensity function analytically from a finite set of moments using inverse moment transform. But Legendre and Zernike moments are most widely used because of minimum redundancy.

The conventional classification of liver images consists of (i) segmentation of normal and abnormal liver of lesion portion from CT liver images; (ii) feature extraction and selection, and (iii) classification. In the proposed approach, as a first step, liver tissues such as normal parenchyma (NP) and hepatocellular carcinoma (HCC) are segmented from arterial phase spiral CT images. In the second step, features are extracted by local binary pattern (LBP), Legendre moments and combined methods. Then the relevant features are selected using sequential feature selection algorithm to reduce the number of features. Finally Euclidean distance is used for classification and images are classified as either normal or abnormal. In this communication, we discuss texture classification of CT liver images using Legendre moments based approach.

Figure 1 shows the framework of the proposed approach. The steps involved in the proposed approach are as follows:

- CT liver images of NP and with HCC with a resolution of 256 grey levels and 512×512 pixel size are collected from the local diagnostic laboratory.

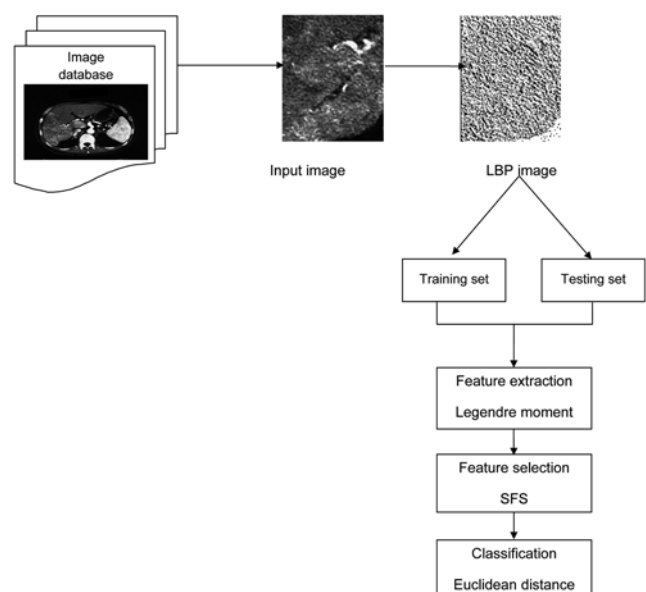


Figure 1. Framework for texture classification of CT liver Images.

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- To detect small-sized tumours, region of interest (ROI) images are partitioned into 8×8 non-overlapping segments and then processed.
- The LBP approach is applied on the processed 8×8 non-overlapping segments and converted to LBP images.
- Legendre moments are applied to extract the texture features and form the feature database, and sequential forward selection algorithm is applied to select the appropriate textural features.
- Finally images are classified using the Euclidean distance classifier and nearest neighbourhood minimum distance decision rule.

In this study, the arterial phase scan of spiral CT abdomen image containing NP and abnormal liver with HCC has been used. A total of 197 ROIs have been sampled – 77 samples belong to HCC with abnormality and 125 samples belong to healthy normal liver. Figure 2 shows the sample images of spiral CT abdomen delineated ROI portion of NP and HCC liver tissues. ROIs are extracted from these images. ROI images are partitioned into 8×8 non-overlapping segments to localized tiny abnormalities. Table 1 shows the image datasets.

Among various texture descriptors, the LBP operator is efficient. It labels the pixels of an image threshold by the neighbourhood of each pixel with the value of the centre pixel and produces the result as a binary number. The LBP method is a complementary measure for local image

contrast and texture features are extracted. The LBP value is computed as

$$LBP = \sum_{i=1}^8 E_i \cdot 2^{i-1}, \tag{1}$$

where

$$E_i = \begin{cases} 1 & \text{if } V_i \geq V_0 \\ 0 & \text{if } V_i < V_0 \end{cases}. \tag{2}$$

The LBP approach defined in eqs (1) and (2) is applied on the ROI extracted images of normal parenchyma and HCC liver and Figures 3 and 4 show the resultant images respectively.

Legendre moments belong to the class of continuous orthogonal moments based on Legendre polynomial. By the orthogonality principle, the Legendre moments for a digital image of pixel size $N \times N$ are defined as

$$L_{pq} = \frac{(2p+1)(2q+1)}{(N-1)(N-1)} \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} P_p(x_i)P_q(y_j)f(x, y), \tag{3}$$

where the functions $P_p(x_i)$ and $P_q(y_j)$ represent the Legendre polynomials of order p and q respectively. x_i and y_j are normalized pixel coordinates in the range $[-1, 1]$. The image coordinates (x, y) are transformed to (x_i, y_j) as

$$x_i = \left(\frac{2x}{N}\right) - 1; \quad y_j = \left(\frac{2y}{N}\right) - 1, \tag{4}$$

where the Legendre polynomial is defined as

$$P_p(x_i) = \sum_{k=0}^p \frac{1}{2^p} \frac{(-1)^{\frac{(p-k)}{2}} (p+k)! x_i^k}{k! \binom{p+k}{2} \binom{p-k}{2}}, \tag{5}$$

with $|x_i| \leq 1$ and $(p - k)$ being even.

The steps involved in classification algorithm are as follows:

1. The Legendre moments for the database images, i.e. ROI extracted LBP images are computed using eqs (3)–(5) to form the feature database.
2. The feature database is created by feature vector as $f_{db} = \{f_1, f_2, \dots, f_N\}$ for the image database consisting of N images. Each feature vector f_i , for $i = 1, 2 \dots, N$, is a set of Legendre moments of order $(p + q)$ as

$$f_i \{L_{00}, L_{01}, \dots, L_{pq}\}_{db}. \tag{6}$$

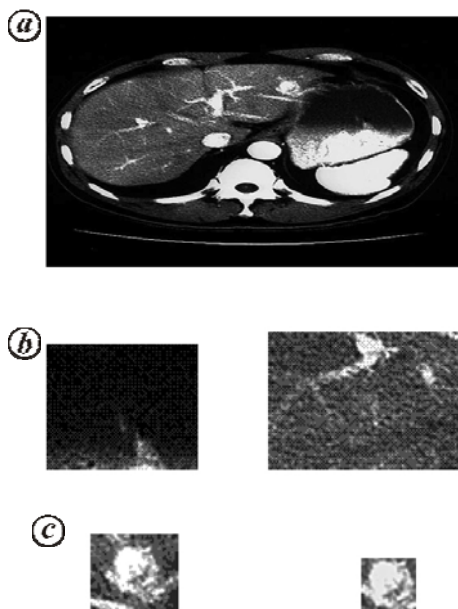


Figure 2. Arterial phase spiral CT scan lesion image with normal and abnormal liver. *a*, Arterial phase spiral CT scans showing a large lesion. *b*, Delineated rectangular region of interest (ROI) of normal liver parenchyma. *c*, Abnormal liver with hepatocellular carcinoma (HCC).

Table 1. Description of image datasets

Tissue type	No. of regions of interest	No. of 8 × 8 segments	Training segments	Testing segments
Hepatocellular carcinoma	200	600	300	300
Normal parenchyma	250	600	300	300

Table 2. Mean feature vectors of local binary pattern (LBP) images of normal parenchyma and HCC liver tissues of Legendre moments

Tissue type	NP	HCC
Legendre moments values		
L_{00}	263.40	279.99
L_{02}	63.05	46.75
L_{04}	326.28	317.52
L_{06}	624.98	634.51
L_{11}	55.70	55.19
L_{13}	125.84	131.31
L_{15}	201.29	194.53
L_{17}	281.54	274.05
L_{20}	107.86	100.33
L_{25}	13.05	20.21
L_{31}	126.84	126.04
L_{33}	300.69	297.37
L_{35}	472.23	479.76
L_{37}	629.86	632.25
L_{40}	278.56	261.70
L_{46}	160.62	166.42
L_{51}	201.39	204.37
L_{53}	471.85	463.99
L_{55}	732.54	736.17
L_{57}	1008.88	1021.20
L_{60}	566.91	560.45
L_{62}	30.02	34.68
L_{64}	193.82	189.65
L_{66}	638.58	662.28
L_{70}	274.80	274.09
L_{73}	639.74	640.96
L_{75}	1007.34	1004.81
L_{77}	1369.05	1375.98

Table 3. Confusion matrix for LBP–Legendre moments reduced feature set

Tissue type	HCC	NP
HCC	285	15
NP	8	292

- The mean feature vector for the database image of all training samples of a particular class is obtained as

$$f = \frac{\sum_{i=1}^N (f_i \{L_{00}, L_{01}, \dots, L_{pq}\})_{db}}{N}, \quad (7)$$

where N is the number of training samples.

- A feature vector comprising Legendre moments of order $(p + q)$ for the query image is formulated

$$f_q \{L_{00}, L_{01}, \dots, L_{pq}\}_{query}. \quad (8)$$

- Distance measure between the feature vector of the query image (f_q) and each feature vector of the database images (f_{db}) is calculated using Euclidean distance

$$D_k(Q_i, D_i) = \sqrt{\sum_{i=1}^n ((f_q)_i - (f_{db})_i)^2}, \quad (9)$$

where n is the number of features, Q_i the query image and D_i the database image.

- All the relevant images are classified to their corresponding classes based on the nearest minimum distance value.

In this experimental study, 450 ROI samples (200 ROIs of HCC and 250 ROIs of NP) of CT liver images are selected from the arterial phase of CT liver abdomen. There are 600 segments (number of 8×8 segments) formed from each tissue type chosen. From these 600 segments, 300 were selected randomly as training set and the remaining 300 constitute the testing set (NP and HCC liver). All the experiments have been implemented in Matlab R2009 and texture characterization of both normal and abnormal tissues has been analysed separately.

An extracted ROI sample belonged to either NP or HCC liver class. Legendre moments-based approach was applied on the LBP image for each tissue type of CT liver images. The selected order 7 of Legendre moments was computed for each of the training samples belonging to both the classes. Sixty-four moment features were extracted which comprise the full feature set. The relevant moment feature vectors were selected using sequential forward selection algorithm. Twenty-eight moment feature vectors were selected using SFS algorithm, which formed the reduced feature set. The mean feature vectors of the normal parenchyma and HCC liver classes were denoted as FV_{NP} and FV_{HCC} respectively. The selected feature vectors of order 7 of Legendre moments are: $L_{00}, L_{02}, L_{04}, L_{06}, L_{11}, L_{13}, L_{15}, L_{17}, L_{20}, L_{25}, L_{31}, L_{33}, L_{35}, L_{37}, L_{40}, L_{46}, L_{51}, L_{53}, L_{55}, L_{57}, L_{60}, L_{62}, L_{64}, L_{66}, L_{70}, L_{73}, L_{75}$ and L_{77} (Table 2). The nearest mean classifier was used to

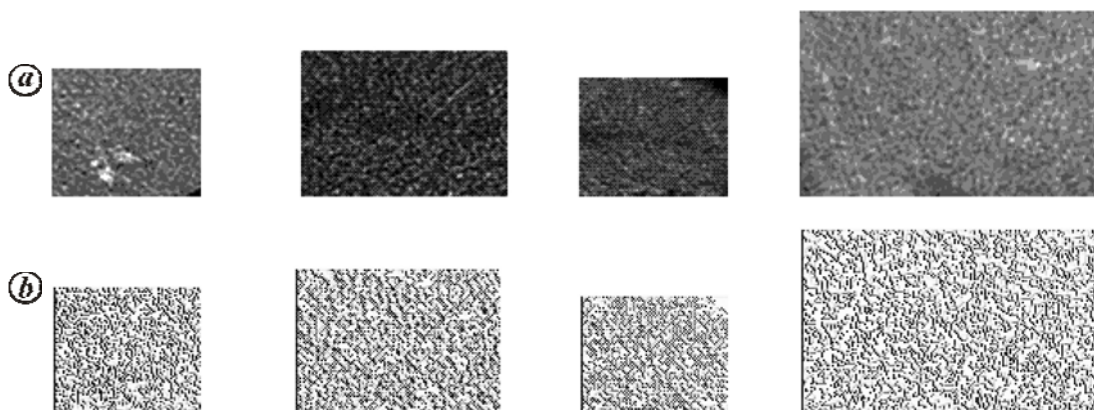


Figure 3. Normal liver and transformation to local binary pattern form (LBP). *a*, ROI portion of normal liver. *b*, Transformed LBP image of normal liver.

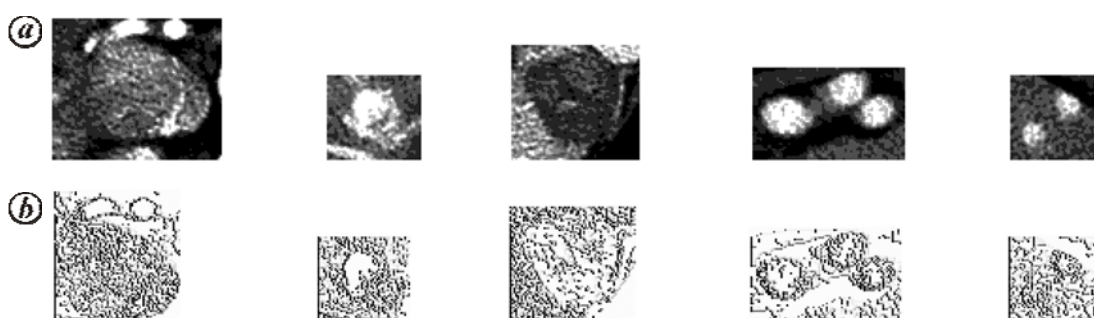


Figure 4. HCC liver and transformation to LBP form. *a*, ROI portion of HCC liver. *b*, Transformed LBP image of HCC liver.

Table 4. Classification accuracy of analysis of texture features of CT liver

Texture features	Number of features	Texture class		Precision (%)		
		Normal	Abnormal	Normal	Abnormal	Average
Legendre moment full feature set	64	273	267	91.00	89.00	90.00
Legendre moment reduced feature set	28	283	272	94.33	90.67	92.50
LBP – Legendre moment full feature set	64	284	280	94.67	93.33	94.00
LBP – Legendre moment reduced feature set	28	292	285	97.33	95.00	96.17

Table 5. Comparative analysis of CT liver classification

Year	Author name	Reference	Features	Classifier	Diseases	Accuracy (%)
2007	Mougiakakou <i>et al.</i>	11	FOS, SGLDM, GLDM, TEM and FDM, genetic algorithm	Five multilayer perception neural networks	HCC, hemangioma, hepatic cysts and normal liver	84.96
2010	Mala <i>et al.</i>	12	42 features – Biorthogonal wavelet and statistical texture feature sequential forward floating search [SFFS] and Genetic Algorithm	Neural network	Fatty liver and cirrhosis	PNN – 96, LVQ – 93 and BPN – 80
2012	Yu <i>et al.</i>	<i>Computational and Mathematical Methods in Medicine</i>	93 features of texture and shape	RLDA, LDP and PCA	HCC, cysts and hemangioma	Triple phase scan – 86.3 and 88
2013	Punia <i>et al.</i>	17		Neural network	Normal and abnormal (HCC, cysts and hemangioma)	96.02

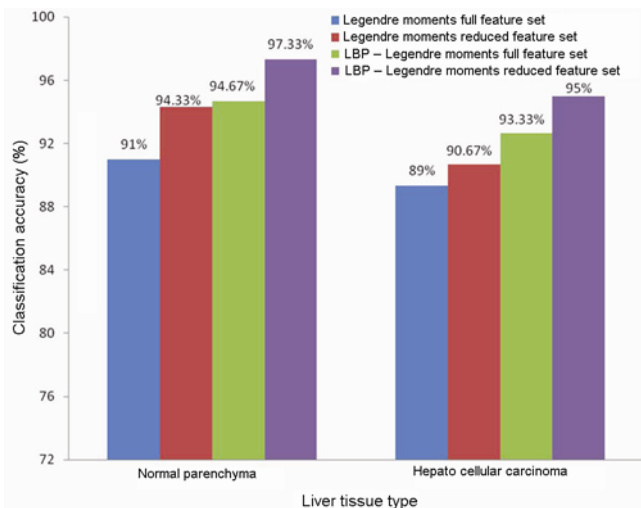


Figure 5. Performance analysis of texture classification of CT liver Images.

classify these samples. The training and testing ROIs of different patients were analysed. Table 3 provides a summary of the results. Table 4 shows the classification accuracy of texture features of CT liver using Legendre moments, while Figure 5 shows the performance analysis. It can be seen that the classification rate is high in LBP–Legendre moments reduced feature set. It is better than the result reported in Table 5, where a comparative analysis of various texture analyses and classification of CT liver images is shown.

The present study showed that Legendre moments have better image representation capability than the traditional continuous moments. So these moments are useful feature descriptors for pattern recognition and classification. The development of a liver tissue classification system has been presented to discriminate two hepatic tissue types from arterial phase of CT abdomen images. A classification performance of 96.17% is obtained using the proposed method. The results revealed that combined features of LBP and Legendre moments reduced feature set and yielded a better classification rate.

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Received 8 August 2014; accepted 30 August 2015

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doi: 10.18520/cs/v110/i4/687-691