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Rotation Invariant Texture Classification using BRINT and GLCM with SVM Classifier

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Abstract: *Texture classification is one of the four problem domains in the field of texture analysis for the development of effective features to extract from a given textured image. This paper proposes a Binary Rotation Invariant and Noise Tolerant (BRINT) which is a very fast, compact and also more accurate while illumination variations, noise and rotation changes. Here Gray Level Co-occurrence matrix algorithm is used along with BRINT for feature extraction. Texture classification is performed with the SVM classification. The proposed method is compared with the existing K Nearest Neighbourhood algorithm. In our proposed work, snake texture has been taken for processing and the proposed method is quantified with various performance metrics like accuracy, sensitivity, specificity and PSNR performance and found to be greater compared with the existing method.*

Keywords*:* Texture descriptors- local binary pattern (LBP), BRINT, Grey Level Co-occurrence Matrix (GLCM) feature extraction, SVM Classification.

INTRODUCTION

TEXTURE is a fundamental characteristic of the appearance of virtually all natural surfaces and is ubiquitous in natural images. Texture classification, as one of the major problems in texture analysis, has received considerable attention during the past decades due to its value both in understanding how the texture recognition process works in humans as well as in the important role it plays in the field of computer vision and pattern recognition [1].

Typical applications of texture classification include medical image analysis and understanding, object recognition, content based image retrieval, remote sensing, industrial inspection, and document classification.

The texture classification problem is conventionally divided into the two sub problems. It is generally agreed that the extraction of powerful texture features is of more importance to the success of texture classification and, consequently, most research in texture classification focuses on the feature extraction part [1], with extensive surveys [1]. Nevertheless it remains a challenge to design texture features which are computationally efficient, highly discriminative and effective, robust to imaging environment changes (including changes in illumination, rotation, view point, scaling and occlusion) and insensitive to noise. Recently, the Bag-of-Words (Bo W) paradigm, representing texture images as histograms over a discrete vocabulary of local features, has proved effective in providing texture features. Representing a texture image using the Bo W model typically involves the following three steps:

(i) Local texture descriptors: extracting distinctive and robust texture features from local regions;

(ii)Texton dictionary formulation: generating a set of representative vectors (*i.e.,* textons or dictionary atoms) learned from a large number of texture features

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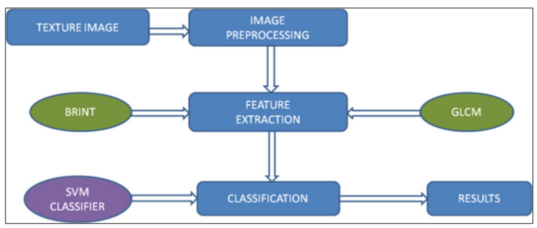
(iii) Global statistical histogram computation: representing a texture images statistically as a compact histogram over

The learned texton dictionary and instability. In contrast, dense approaches, applying texture descriptors pixel by pixel are more popular. Important dense textures descriptors include Gabor wavelets [8], LM filters [5], MR8 filters [5], BIF features [7], LBP [2], Patch descriptor [6] and RP random features [3] and many others [4].fingerprint matching, visual inspection, image retrieval, biomedical image analysis, face image analysis, motion analysis, edge detection, and environment modeling [8]–[11]. Consequently many LBP variants are present in the recent literature. Although significant progress has been made, most LBP variants still have prominent limitations, mostly the sensitivity to noise , and the limiting of LBP variants to three scales, failing to capture long range texture information. Although some efforts have been made to include complementary filtering techniques , these *increase* the computational complexity, running counter to the computational efficiency property of the LBP method. In this paper, we propose a computationally simple approach, the Binary Rotation Invariant and Noise Tolerant (BRINT) descriptor, which has the following outstanding advantages: It is highly discriminative, has low computational complexity, is highly robust to noise and rotation, and allows for compactly encoding a number of scales and arbitrarily large circular neighborhoods. At the feature extraction stage there is no prelearning process and no additional parameters to be learned.

Proposed Methodology



Fig(a) Block Diagram of Proposed Methodology

The input texture image undergoes pre-processing by applying Gaussian filtering to remove the noise from the image. Gaussian filter is windowed filter of linear class, by its nature is weighted mean. The Gaussian Smoothing Operator performs a weighted average of surrounding pixels based on the Gaussian distribution. Then the features are extracted using BRINT and GLCM Feature Extraction methods. Each pixel values are extracted for BRINT as red, green, blue separately. From these values Histograms are generated to analyses the peak values. Similarly same procedure is done for GLCM and the features are extracted successfully from the Image. After the Feature Extraction, Classification is done using SVM (Support Vector Machine) Classifier. Texture classification method involves two phases: the learning phase and recognition phase. In the learning phase, a set of textural feature are extracted for each image. In the recognition phase, the textural features of the sample are compared to those of the training images and the sample is assigned to the category with the best match. If the best match is found, the sample is accepted otherwise it is rejected.

PROPOSED ALGORITHMS - BRINT, GLCM AND SVM

Motivation

The proposed BRINT is based on the concept of local binary pattern (LBP) and Completed Local Binary Pattern (CLBP). LBP operator leading to poor discriminant power and large storage requirements. The LBP operator captures only the very local structure of the texture of database. So it is difficult to collect information from a larger area. CLBP is leading to perform an even higher dimensionality so this system not applicable for storage and reliable classifier learning. These descriptors having one of the noise sensitivity, and information insufficiency. For KNN Algorithm, large value of K gives good performance. But for large K more neighbours are required and hence larger the computing time.

BRINT Algorithm

The BRINT feature vector, in its simplest form, is created in the following manner:

- Divide the examined window into cells (e.g. 16x16 pixels for each cell).
- For each pixel in a cell, compare the pixel to each of its 8 neighbours (on its left-top, left-middle, left-bottom, right-top, etc.). Follow the pixels along a circle, i.e. clockwise or counter-clockwise.
- Where the centre pixel's value is greater than the neighbour's value, write "1". Otherwise, write "0". This gives an 8-digit binary number (which is usually converted to decimal for convenience).
- Compute the histogram, over the cell, of the frequency of each "number" occurring (i.e., each combination of which pixels are smaller and which are greater than the center).

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- Optionally normalize the histogram.
- Concatenate (normalized) histograms of all cells. This gives the feature vector for the window.

GLCM Algorithm

The algorithm comprises of four main steps, which are

- Decomposition of the gray level image into sub-bands
- Partitioning the textured image into non-overlapping sub-windows
- Extracting co-occurrence features and finally classifying each sub-window as defective or non-defective.
- A histogram is computed from the desired GLCM

SVM Classification Algorithm

Classification using SVM (Support Vector Machine) Classifier is done in the following manner.

- Classify the texture based on the extracted features using SVM classifier.
- In the SVM classifier there are two phases such as train phase and test phase.
- In train phase, train the all dataset features with mentioned label.
- Hyper plane formed with trained features where each hyper plane represented the each group.
- That each grouped train features are labeled at the end of train phase.

RESULTS AND DISCUSSIONS

In pre-processing we are applying Gaussian filtering to our input image. Features are extracted using BRINT and GLCM. Extraction can be done for various noise levels. Each pixel values are extracted for BRINT as red, green, blue separately. From these values Histograms are generated to analyze the peak values. Similarly same procedure is done for GLCM Thus features are extracted successfully from the Image. After the Feature Extraction, Classification is done using SVM (Support Vector Machine) Classifier. Snake Textures have been taken for experimental analysis.

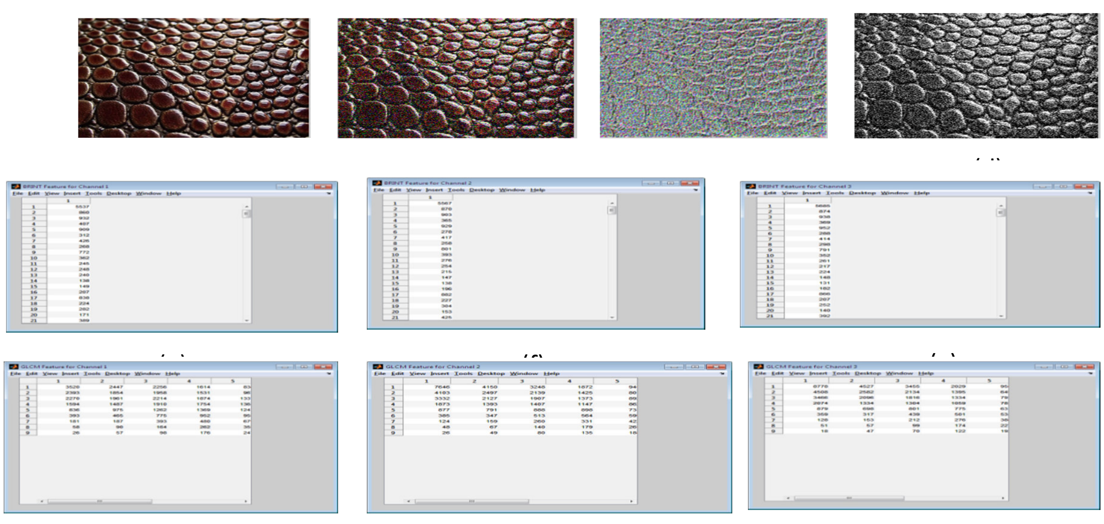

Fig 2:(a) Input Image (b) Filtered Image (c) BRINT Image (d) GLCM Image (e) BRINT Feature Extraction for channel1 (f) BRINT Feature Extraction for channel 2 (g) BRINT Feature Extraction for channel 3 (h) GLCM Feature Extraction for channel 1 (i) GLCM Feature Extraction for channel 2 (j) GLCM Feature extraction for channel 3.

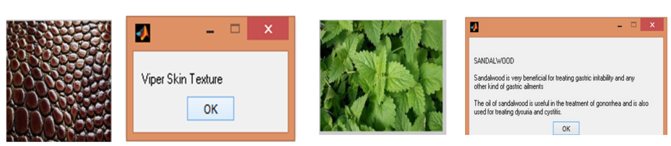

Fig (3) SVM

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Performance Comparison

The performance of the proposed method is quantified by calculating various performance metrics like Classification Accuracy, Sensitivity, Specificity and PSNR Performance and is compared with existing KNN Algorithm. The performance metrics values are found to be greater compared to the existing method.

The Classification Accuracy A_i depends on the number of samples correctly classified and is evaluated by the formula

$$A_i = \frac{t}{n} * 100 \qquad (1)$$

where t- number of samples correctly classified, n- total number of samples.

The Sensitivity measures the proportion of positives that are correctly identified as such and is defined as

$$S_n = \frac{TP}{TP + FN} \qquad (2)$$

where TP-True Positive, FN-False Negative

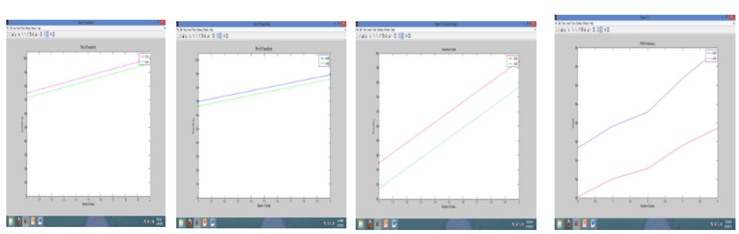
The Specificity measures the proportion of negatives that are correctly identified as such and is defined as

$$S_p = \frac{TN}{TN + FP} \qquad (3)$$

where TN-True Negative, FP-False Positive

PERFORMANCE MEASURE	k-NN (%)	SVM (%)
ACCURACY	85	98.889
SENSITIVITY	75	98
SPECIFICITY	70	80.5
PSNR PERFORMANCE	80	85.5

Table 1.Performance Comparison Table



(a) (b) (c) (d)

Fig(4) Performance Comparision Graphs- (a) Plot of Sensitivity (b) Plot of Specificity (c) Plot of Accuracy (d) Plot of PSNR Performance.

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CONCLUSION

The proposed BRINT descriptor together with GLCM is shown to exploit very good performance on texture databases under both normal conditions and noise conditions. The extracted features undergo SVM Classification. The Proposed method is compared with the existing KNN Algorithm. The performance of the proposed algorithm is quantified by calculating various performance metrics like Classification Accuracy, Sensitivity, Specificity and PSNR Performance. The Classification Accuracy, Sensitivity, Specificity and PSNR Performance are found to be 14%, 23%, 11%, 6% greater respectively compared with the existing KNN Algorithm.

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