Texture Feature Extraction using Relaxed Local Ternary Pattern and Gabor Local Binary Pattern for Object Recognition

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Abstract: Object recognition plays a vital role in computer vision and image processing. For the objects in an image there are several features that form the interesting points on the object which might be extracted to give a feature description of the object. This description obtained from the training image could be utilized to find the object when trying to locate the object in the query image that contains several other objects. Thus effective feature extraction techniques are essential in order to correctly classify the objects. In this paper, two sorts of edge-texture feature extraction techniques such as Gabor Local Binary Pattern (GLBP) and Relaxed Local Ternary Pattern (RLTP) has been proposed to recognize objects.

Keywords: object recognition, feature extraction, Gabor Local Binary Pattern (GLBP), Relaxed Local Ternary Pattern (RLTP).


1 Introduction

Object recognition is a technique of identifying an object in an image [1]. Object recognition plays a significant role in various fields such as fault diagnosis system, leaf species detection and surveillance system and so on. In particular the object recognition system comprises of several stages among which feature extraction is considered as the most important. The intent of feature extraction is to extract and provide pertinent features for the classification or recognition process as the classification accuracy [2, 3] relies on the quantity of the features extracted from the image.

The object recognition features can be represented either in sparse [4] or dense representation form. The sparse feature representation utilizes the interest point detectors to find the structures like roundish mass around the object and the corners. The dense representation is extracted from a fixed location density in a recognition window. Each object has various texture and shapes that are characterized using edge and texture information.

Texture is the widespread property of several physical surfaces in the real world. Thus, texture is a vital cue for various computer vision applications such as image segmentation and classification. The prime purpose of texture feature extraction is to acquire the relationships between the pixels that belong to a related texture like spatial gray level dependence. These relationships let to distinguish between every unique texture from others. Several techniques have been developed in recent years to describe, classify and retrieve the texture images.

In this paper, Gabor Local Binary Pattern (GLBP), Relaxed Local Ternary Pattern (RLTP) approaches have been employed to extract the texture features. The extracted features are then fed into the SVM classifier to accurately classify the objects.

II. Related Work

In [5] improvement has been made in the feature extraction process using the Local Binary Pattern (LBP) approach. Here two distinct LBP histograms are built for edge pixels and other for non-edge pixel. The final feature vector is constructed using the weighted combination of the two histograms. The results indicate that the improvement made on the LBP approach has presented better accuracy than the original approaches. [6] Presented a novel approach for classification color texture features extracted using GLCM estimated from the LBP images. The LBP images extracted from the color texture images are encoded in 28 diverse color spaces. An iterative process then chooses the discriminative features between the extracted features to construct a low dimensional feature space. [7] Proposed an
approach to extract image texture features for classification. This approach comprises of two sets of features such as DLBP (Dominant Local Binary Pattern) for texture features in the image and the supplementary features are extracted utilizing the circularly symmetric Gabor filter responses. The DLBP approach utilizes the most commonly occurred patterns to obtain the descriptive texture information whereas the Gabor based features aims at providing supplementary global texture to the DLBP features. A novel image feature based on spatial co-occurrence between micropatterns has been proposed, in which each micropattern is characterized by a LBP [8]. In this approach all the micropatterns LBP’s are combined into a single histogram. This discards the vital information regarding the spatial relations between the LBPs, though they may comprise the information about the global structure of the image. An approach based on continuous wavelet transform and local binary pattern has been proposed for content based image classification. Here the LBP is improved by using the wavelet transformation approach. Here 12 classes of Brodatz textures database has been utilized for experimental purpose and the each class is subdivided into 64 texture images and the wavelet transformation is applied to every texture. Once the texture is transformed using wavelet feature matrix is formed using the LBP. The same notion is employed at the LBP computation that generates 9 LBP patterns. Then 9 LBP histograms are computed that are utilized as feature vector for the classification of the image.

III. Edge-Based Texture Feature Extraction

A. Gabor Local Binary Pattern (Glbp)

The Gabor local binary pattern presents robustness to variations such as noise and illuminations by combining LBP, local region histogram [10] and Gabor transform. The GLBP operator is a combination of Gabor wavelets and the local binary pattern operator [11] which can be defined as

$$GLBP^v_\mu(z) = \sum_{p=0}^{N-1} S(a^v_\mu(z_p) - a^v_\mu(z)) 2^p$$

Here $z=(x, y)$ and $a^v_\mu(z)$ is the $j^{th}$ element of $A^v_\mu(z) = f(z)^* \varphi^v_\mu(z)$ represents the gray level distribution of the image $f(z)$ with the Gabor wavelet. Here $v$ and $\mu$ are the scale and orientation of the Gabor wavelets. In this study, five scales and eight orientations were employed.

The process of representing the image with GLBP comprises of three steps. Initially, the GLBP operators are performed on the image to construct multi-scale and multi-orientation GLBP images. Then the histogram is extracted from every GLBP local images to generate the local representation of the image. Finally all the histograms are integrated into a single feature vector to construct the global representation.

B. Relaxed Local Ternary Pattern

The local binary pattern translates the pixel difference between the center pixel and the neighboring pixel. The local binary pattern is susceptible to noise so a small image noise causes the difference coded from 1 to 0 or vice versa. The local ternary pattern is less susceptible to noise as it translates the small pixel difference into a distinct state. The local ternary pattern code is acquired as

$$LTP_{N,M} = \sum_{i=0}^{N-1} s'(i_p - i_c) 3^i$$

Where $(z-t)$ which is defined as

$$s'(z-t) = \begin{cases} 1 & -t \leq z \leq t \\ 0 & t < z \leq \infty \end{cases}$$

Though, a substantial amount of information might be lost during this process. Further the positive and negative LBP histograms are strongly correlated, thus a huge volume of redundant information may exists in these two histograms. In order to overcome the issue of LBP and LTP relaxed LTP has been proposed. In relaxed LTP instead of coding the pixel difference as 0 or 1, the probability of coding is assigned. Provided the pixel difference z, the probability to encode the pixel as 1 is denoted as $p^+(z)$ and the probability to encode it as zero is denoted as $p^0(z) = 1 - p^+(z)$. In RLTP the ambiguous state is coded as 1 and 0 with equal probability which is formulated as

$$p^+(z) = \begin{cases} 1 & z \geq t \\ 0.5 & |z| < t \\ 0 & z \leq -t \end{cases}$$

When building the LBP histogram, the probabilities of the entire 256 pattern is defined as

$$p_i = \prod_{k=0}^{2^i-1} c_i + 2^k$$

The LBP code $f = \sum_{i=0}^{2^i-1} c_i 2^i_c$ is the codes $i^{th}$ code, $p_1 i(z)$ and $p_0 i(z)$ are the probabilities that the $i^{th}$ bit should be coded as 1 and 0. The probabilities of the entire pixels within a single patch are summed up to form the LBP histogram of the image area.

IV. Classification

The extracted features are then fed into the SVM [12] classifier to accurately the objects. Support vector machines are supervised learning approach with associated learning algorithms that explore the data and identify patterns, employed for regression analysis and classification. Given the training samples, each labeled as belonging to one of the two classes, the SVM training algorithm constructs a model...
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that allocates new patterns into one of the classes. The SVM model is the representation of the samples as points in the space that are mapped, so that the samples of the distinct classes are divided by a line that is as wide as possible. The new samples are then mapped to the same space and calculated to belong to a certain class based on the side of the line they fall.

The SVM constructs a hyperplane in high dimensional space that is utilized for classification. Fig 1 illustrates the SVM classification. The hyper planes in the higher dimensional space are described as a set of points that dot product of whose is assumed to be constant. The vectors describing the hyperplane are selected to be linear combination with parameters $\alpha_i$ of image feature vectors that are contained in the database.

$$\sum \alpha_i k(x_i, x) = \text{constant} \quad (6)$$

The algorithm assumes $n$ samples from two classes: $(x_1,y_1),\ldots,(x_n,y_n)$ where $x_i \in \mathbb{R}^n$ and $y_i \in \{1,0\}$

V. Results And Discussion

A graph is plotted to analyze the performance of the new algorithm Relaxed Local Ternary Pattern. From fig 2, it is clear that conventional LBP has much lower performance than Relaxed Local Ternary Pattern. DRLBP and DRLTP perform better in terms of object recognition as compared to LBP. But, their response is poor when compared with Relaxed Local Ternary Pattern.

Table 1 shows the values of features extracted from a set of 10 images. It is seen that Gabor Local Binary Pattern and Relaxed Local Ternary Pattern have much higher values, which in turn is a proof for their increased efficiency. Gabor filter is an ideal tool to this end, which can calculate the difference between regions covered by its support. The magnitude values of the Gabor transform change very slowly with displacement, so they can be further encoded. In order to enhance the information in the GMPs, encode the magnitude values with LBP operator.

Table 1 Comparison of Feature Values

<table>
<thead>
<tr>
<th>TEST SET NUMBER</th>
<th>FEATURE VALUES</th>
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<tbody>
<tr>
<td></td>
<td>LBP</td>
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<tr>
<td>1</td>
<td>2.1968</td>
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<tr>
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<td>10</td>
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Table 2. Performance Comparison

<table>
<thead>
<tr>
<th>APPROACH</th>
<th>PERFORMANCE IN PERCENTAGE</th>
<th>ACCURACY IN PERCENTAGE</th>
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<tbody>
<tr>
<td>LBP</td>
<td>56.9</td>
<td>66.7</td>
</tr>
<tr>
<td>DRLBP</td>
<td>60.9</td>
<td>77.2</td>
</tr>
<tr>
<td>DRLTP</td>
<td>73.1</td>
<td>81.1</td>
</tr>
<tr>
<td>GLBP</td>
<td>82.1</td>
<td>89.3</td>
</tr>
<tr>
<td>RLTP</td>
<td>85.5</td>
<td>91.4</td>
</tr>
</tbody>
</table>
VI. Conclusion

Object recognition plays a vital role in computer vision and image processing. For the objects in an image there are several features that form the interesting points on the object which might be extracted to give a feature description of the object. This description obtained from the training image could be utilized to find the object when trying to locate the object in the query image that contains several other objects. Thus effective feature extraction techniques are essential in order to correctly classify the objects. In this paper, two sorts of edge-texture feature extraction techniques such as Gabor Local Binary Pattern (GLBP) and Relaxed Local Ternary Pattern (RLTP) has been proposed to recognize objects. The performance of the proposed approach is compared with the existing LBP, DRLBP and DRLTP approaches. The results show that the proposed outperforms the existing LBP, DRLBP and DRLTP approaches.

References