Discriminative Robust Local Binary Pattern based Edge Texture Features for Object Recognition

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Abstract: ***Local Binary Pattern proves to be the most popular texture classification feature. The proposed system provides edge texture features, Discriminative robust Local Binary Pattern for the recognition. The algorithm used retains the contrast information and solves the issues of Local Binary pattern, Local Ternary Pattern and Robust Local Binary Pattern for proper representation. K-Nearest Neighbor classification and Surf matching techniques are used for classification and matching. The edge texture features obtained from the input image are stored and the image is retrieved based on the features extracted for the object of user's interest. The new features are found robust to the image variations that are caused due to intensity inversion and are discriminative to the image structures within the histogram block. Local Binary Pattern is robust to the illumination and contrast variations. The proposed features also tend retain contrast information that is necessary for proper representation of the object contours.***

Keywords: Local Binary Pattern, Local Ternary pattern, K nearest neighbor classifier, Speed up robust feature

1. Introduction

Texture classification has become an active research topic in the computer vision and pattern recognition. Early texture classification methods were also focused on the statistical analysis of texture images. Interest-point detectors are been used in sparse feature representations. It helps to identify the structures like corners and blobs on the particular object. A feature is created which is necessary for the image patch that tends to be around each point. Various feature representations that include Principal Curvature-Based Regions, Scale Invariant Feature Transform, Local Steering Kernel , Speeded Up Robust Feature, Region Self-Similarity features, sparse parts-based and Sparse Color representation. At fixed locations, dense feature representations are extracted densely in a detection window, which are gaining popularity as they tend to describe objects richly when they are compared to the sparse feature representations. Other feature representations Such as Local Ternary Pattern (LTP), Wavelet, Local Binary Pattern (LBP), Extended Histogram of Gradients, Local Edge Orientation Histograms, Geometric-blur and Feature Context have been proposed over recent years. Dense Scale-Invariant Feature Transform has also been proposed to help alleviate the problems in sparse representation. A similar feature is obtained for some different local structures. Hence, it becomes difficult to differentiate these local structures. Various different objects are of different shapes and textures. Hence, it becomes desirable to represent objects using both edge and texture information. Further, in order to be robust to the contrast variations and illumination, Local Binary Pattern (LBP), Local Ternary Pattern (LTP) and Robust Local Binary Pattern do not tend to provide discrimination between a weak contrast local pattern and strong pattern. There are various object recognition challenges. The objects are to be detected against the cluttered and noisy backgrounds along with the other objects under contrast environments and different illumination. It tends to be a crucial step in the object recognition system to obtain proper feature representation as it improves performance by providing discrimination between the object from the background or the other objects that are in different lightings and different scenarios.

2. Related work

According to reference [1], J. Yuan, J. Ren and X. Jiang have proposed a noise-resistant LBP (NRLBP) preserves the local structures in image with the presence of noise. The small pixel difference seems to be vulnerable to noise. Thus, it is encoded as an uncertain state first to further determine its value based on the other bits of the Local Binary Pattern code. Among various other structures most of the image local structures are represented by the uniform codes and also noise patterns which is widely accepted and they most likely fall into non-uniform codes. Thus, here the value of an uncertain bit is assigned so as to form possible uniform codes. They develop an error correction mechanism in order to recover the distorted image patterns.

In reference [4], the paper describes a general framework for the texture analysis which we refer as the Histograms of equivalent patterns. The histogram of equivalent pattern provides a clear and unambiguous mathematical definition that it is based on the partition of the feature space which is also associated to image patches which consist of a predefined size and shape. In order to achieve this task the local or global functions are defined of the pixels intensities.

In this correspondence [5], a modeling of the (LBP) local binary pattern operator is been proposed and a complete Local Binary Pattern (CLBP) scheme is been developed for the texture classification. Center pixel is used to represent a local region and a local difference sign-magnitude transform.

In reference [8], a novel and efficient facial image representation is proposed which is based on local binary pattern texture features. The face image is been divided into several regions for computation from which the Local binary Pattern feature distributions are to be extracted and further

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they are concatenated into an enhanced feature vector that can be used as a face descriptor in the algorithm.

Despite of the excellent performance by Local Binary Pattern (LBP) in the texture classification as well as in face detection, its performance parameter in human detection has been limited. Local Binary Pattern differentiates a bright human that considers as object from a dark background and vice-versa. Due to this there is increase in the intra-class variation of humans.. Non-Redundant Local Binary Pattern (NRLBP) was proposed in order to solve the first issue of Local Binary Pattern. The Local binary pattern texture method is considered as the most successful method for face recognition. Due to the success of Local Binary Pattern, recently many models, which are variants of Local Binary Pattern are been proposed for texture analysis.

3. Proposed system

We have proposed a novel edge-texture feature for recognition that provides discrimination which is Discriminative Robust Local Binary Pattern and Local Ternary Pattern. Discriminative Robust Local Binary Pattern and Local Ternary Pattern help in discrimination of the local structures that Robust Local Binary Pattern seems to misrepresent. Also, the proposed features tend to retain the contrast information of the image patterns. They comprises of both edge and texture information which seem desirable for object recognition. K Nearest Neighborhood classifier is been used to provide image classification.

An object has 2 distinct states for differentiation from other objects - the object surface texture and the object shape formed by its boundary. The boundary often shows much higher contrast between the object and the background than the surface texture. Differentiating the boundary from the surface texture brings additional discriminatory information because the boundary contains the shape information. Local Binary Pattern does not provide differentiation between a weak contrast local pattern and a strong contrast pattern. It mainly captures the object texture information. The histogramming of LBP codes only considers the frequencies of the codes i.e. the weight for each code is the same. This makes it difficult to provide differentiation between a weak contrast and a strong contrast local pattern. To mitigate this, we propose to fuse edge and texture information together in a single representation by further modifying the way the codes can be histogrammed. Figure 1 shows Block Diagram representation.

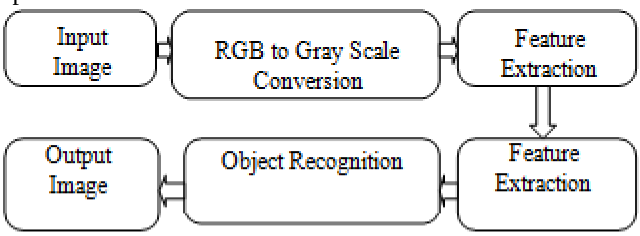

Figure 1: Block Diagram

For the Input, the image is selected from the database and edge texture features are extracted. Object from the image is cropped for recognition provided with its features. KNN classifier is used for Image Classification. In k-NN classification, the output seems to be a class membership. An object classification is done by a majority vote of its own neighbors, with the object to be assigned to the class which is most common among its k nearest neighbors. Figure 2 shows the Flow of the proposed system.

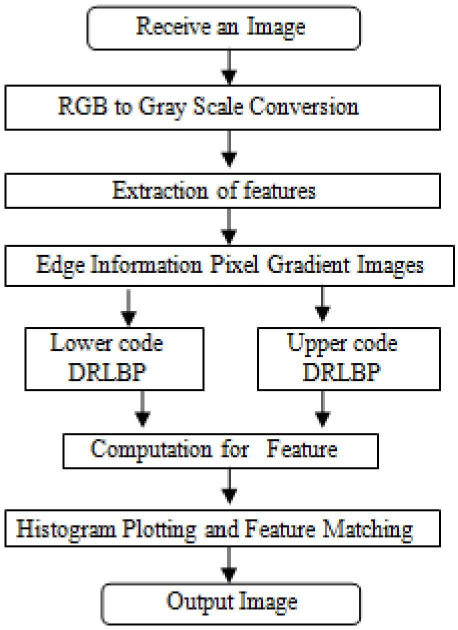

Figure 2: Flowchart

4. Evaluation

Figure 3 shows the basic Graphical User Interface of the proposed system. It uses MATLAB software for simulation. It provides a comprehensive set of reference standard algorithms, functions, and apps for image processing, analysis, visualization, and algorithm development.

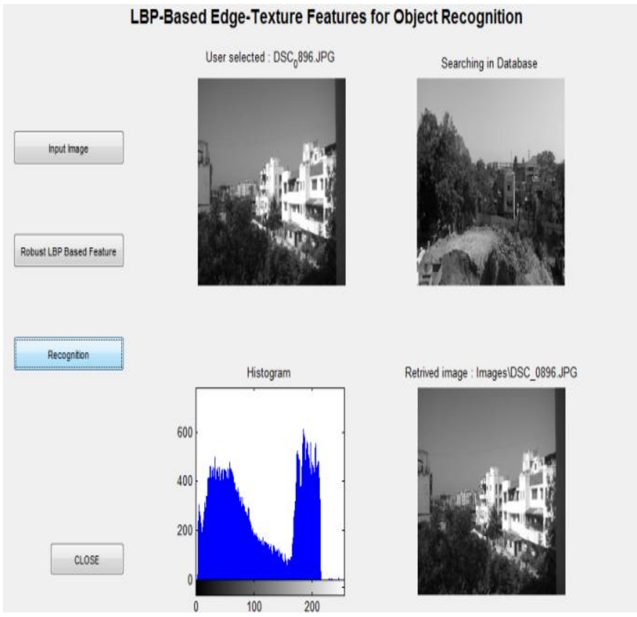

Figure 3: Basic GUI

The edge texture features are obtained using the DRLBP algorithm shown in Figure 4

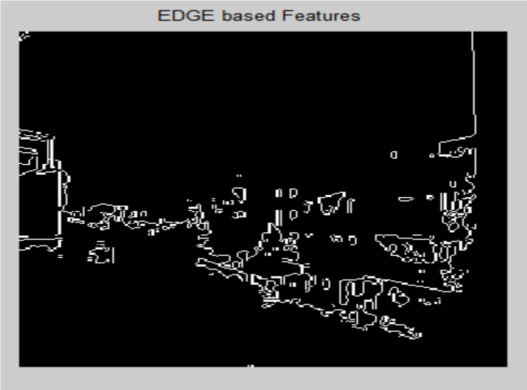

Figure 4: Edge based Features

The Local Binary Pattern Histogram along with the LBP values are obtained by simulation is as shown in figure 5 and figure 6

INPUTS <18x256 double>

	1	2	3	4	5	6	7	8	9	10	11	12
1	1168	141	901	361	154	30	333	447	419	201	112	581
2	924	142	214	256	175	58	197	516	382	258	45	520
3	1367	226	1038	415	209	43	398	617	619	317	161	592
4	1810	219	654	237	262	40	256	362	743	278	121	450
5	875	124	504	210	115	31	301	499	256	166	53	782
6	1666	274	549	225	265	57	218	427	546	220	86	390
7	574	89	345	72	81	7	73	139	222	52	23	96
8	1457	262	345	222	290	60	231	690	756	305	72	496
9	379	71	164	131	80	8	117	223	98	96	29	366
10	2177	242	787	352	248	56	371	366	453	304	94	453
11	2205	222	762	355	281	50	378	365	403	301	109	475
12	2199	259	723	363	268	36	394	367	396	346	84	478
13	2181	246	731	343	262	54	386	358	363	349	115	504
14	1157	199	818	428	201	24	358	764	457	405	84	896
15	1203	205	835	388	183	29	374	776	467	397	81	967
16	1147	199	854	413	161	35	388	802	461	370	92	936
17	1243	92	288	157	73	16	166	846	902	280	57	408
18	1276	87	247	138	69	27	190	857	905	261	70	399
19												

Figure 5: Local Binary Pattern Features

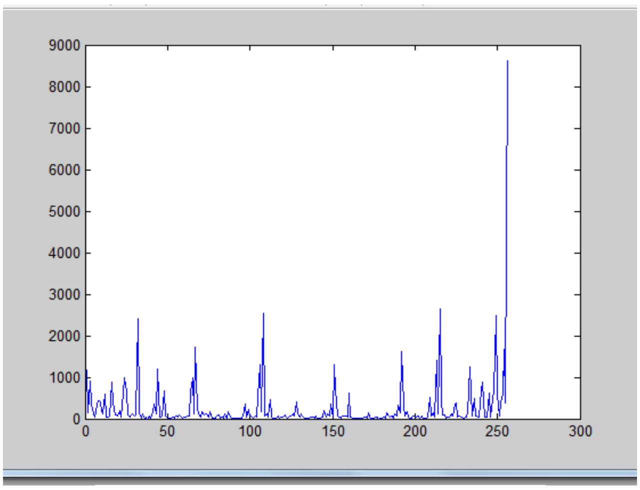

Figure 6: Local Binary Pattern Histogram

Speed up Robust Feature is a detector and a descriptor which provides points of interest in the images where the image is further transformed into coordinates by using the multi-resolution pyramid technique. This particular technique ensures that the points of interest tend to be scale invariant. Figure 7 Shows feature points using Surf.

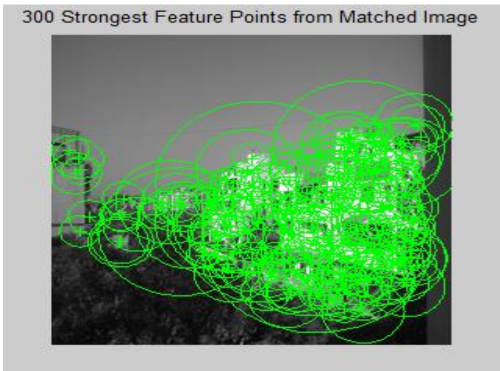

Figure 7: Strongest Feature points

Figure 8: Matched points

5. Conclusion

The features extracted are found robust to image variations that are caused due to the intensity inversion and they also provide discrimination to the image structures which are within the histogram block. The Interclass variations are also reduced. The Proposed system provides efficient recognition and helps to alleviate the issues of Local Binary Pattern, Robust Local Binary pattern and local ternary pattern.

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