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Research Article

Rotation Scale Invariant Texture Classification for a Computational Engine

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Abstract: Texture analysis is a highly significant area in the arena of computer vision and connected pitches. Not the least, classification is also equally important and laudable zone in the area of understanding the texture pattern and is gaining a lot of interest among the researchers in the field of computer vision. It finds a widespread application in area of pattern classification, robotic applications, textile industries etc. In this study, rotation invariant texture has been analyzed and a novel Rotation scale invariant texture classification algorithm has been proposed and tested which is found to be very efficacious and improved results are obtained with the same. The proposed algorithm has been made to undergo testing with standard data sets as UMD dataset, Vision Texture (VisTex), UIUC dataset. The results are discussed clearly with a line of justification being drawn.

Keywords: Invariant texture classification, texture, texture classification, texture data sets

INTRODUCTION

One can simply identify a lot of applications for the texture analysis in the field of computer vision by Haralick *et al*. (1973). After a careful review, it has been understood that, in the past couple of decades, texture has been widely used in the areas of object recognition, segmentation and scene interpretation. Also there is an exceptional application opportunities found in industrial automation, robotics and medicine sectors. Humans are no different and the visual system of human uses the texture for interpreting and recognizing the images. For a clearer understanding, defining Texture becomes inevitable. There are lots of definitions available in the technical world. Best of them have been handpicked and presented below for perusal. According to Longman dictionary, Texture is "something composed of closely interwoven elements or an organization of constituent particles of a body or substance; and the visual or tactile surface characteristics and appearance of something (e.g., fabric). The next focus area is on the methodologies used for texture classification. Before someone goes for texture classification, extracting the features becomes inexorably important. The extracted features are the channels which would be useful in understanding the properties of the surface and then can be classified. The texture classification can be visualized as three stage process as shown in the Fig. 1.

Stage-1 is where the texture input image is being fed into the system. Feature extraction is the next subsequent stage where properties of the texture input image can be extracted in terms of measurable parameters. The texture feature extraction can be classified into two categories structural and statistical texture. A structured approach sees an image texture as a set of primitive Texels in some regular or repeated pattern. This works well when analysing artificial textures. Texel is defined as the fundamental unit of texture space. To obtain a structured description a characterization of the spatial relationship of the texels is gathered by using Voronoi tessellation of the texels. In statistical texture analysis, texture features are computed from the statistical distribution of the observed combinations of intensities at positions relative to each other in the image. According to the number of intensity points (pixels) in each combination, statistics are classified into first-order, second-order and higher-order statistics. In the proposed approach second order statistical measure of texture for the images are considered. Then, all these extracted parameters are then classified with a classifier algorithm. The extracted features are very vital for the classification to happen precisely. Texture classification is the chore of recognizing an Identical textures in all directions at different surface alignments. In the previous era of image processing the texture classification has been done much based on the statistical based approach of the input texture images. The methods can be co-occurrence matrix by Carr and De Miranda (1998) and the filtering based approaches and have been researched by Haralick *et al*. (1973) and Randen and Husy (1999), respectively. These methodologies fetches excellent results if texture input images have comparable or undistinguishable orientations. This might not be suitable for the real-world scenarios. One would need "robust rotation invariant features" in any application for acquiring best classified results and this is not an

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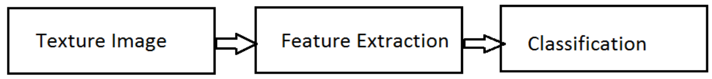

Fig. 1: Stages of texture classification

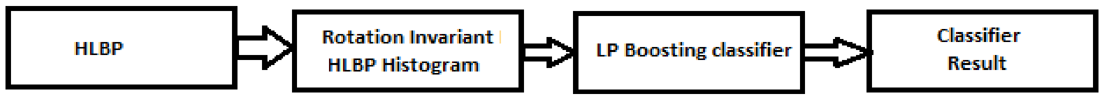

Fig. 2: Proposed algorithm

easy take away task. Rather, it has lot of challenges embedded in it. Though it is observed that there are many methods available for rotation invariant texture features, it is extremely challenging to spot the best out of it. So the classification can be done as statistical methods by Wu and Wei (1996) and Model based methods. In the former the images are characterized with the random properties of the spatial distribution of grey levels. In the latter, a model to the texture image has been applied and the classification algorithm of the image has been derived.

This research study presents a rotation scale invariant LP boosting based texture classification and the same uses Haar local binary pattern as a texture feature descriptor. A block diagram has been presented below in Fig. 2 and the same can be taken as reference for understanding the proposed algorithm.

Proposed algorithm-Rotation Scale Invariant Texture Classification (RSITC algorithm): First stage of the proposed algorithm is HLBP, expanded as Haar Local Binary Pattern is playing a vital role in the proposed algorithm. It is observed that wavelet based texture descriptors are very sensitive to illumination. LBP (Local Binary Pattern) is very much resistive to illumination variations. HLBP features combine both Haar wavelets and LBP features, thereby forming an excellent choice and produces good results in rotation and scale invariants by Deng and Clausi (2004) and Campisi *et al*. (2004). HLBP is being calculated in two different stages. The stage one is helpful in evaluating LBP followed by stage 2 where HLBP is getting calculated. The input is a considered to be an M*N 8 bit gray level Image (I). The LBP Image ILBP is calculated from original image I. LBP can be applied at different scales. The LBP feature vector has the following steps embedded in its creation and are summarized below.

The gray level image is divided into non-overlapping blocks (Let Xm, Ym be the centre of each block). Each and every pixel in the blocks is compared with 4 of its neighbours (I (Xi, Yi)):

$$\text{ILBP}(Xm, Ym) = \sum i = 0 \text{ to } 3\ S(I(Xi, Yi) - I(Xm, Ym)).2n$$

The function s (x) can be defined as:

$$s(x) = \begin{cases} 1 \text{ if } x >= 0 \\ 0 \text{ if } x < 0 \end{cases}$$

The next step in the entire process is to calculate the integral histogram set of LBP image. {IkH} K, Where, K ε {1, 16}. Integral histogram set entail 16 integral histograms. The subsequent step is to calculate the Integral Histogram (IkH) is defined as follows:

$$\text{IkH}(x, y) = \sum \text{Sk}(u, v)$$
$$u <= x,\ v <= y$$

The function S_k can be defined as:

$$S_k = \begin{cases} 1 \text{if } I_{LBP}(u, v) = k \\ 0 \text{ Otherwise} \end{cases}$$

The third stage of proposed algorithm is discussed here in this section. HLBP feature is defined as follows with the sequence:

$$I(\text{HLBP})_{T, K, x, y, w, h, \theta, p}(I)$$

where,
T = The mask type
K = The LBP label

Position (x, y) of the mask inside the image plane.

w, h = Remain as size of the mask
θ = The threshold value
p = The direction

The further processing will be with the following ladders.

Step 1: (w, h) is to be positioned on the LBP image at the position (x, y).

Step 2: The positive A+ and negative A- are the two mask regions of each mask type. Representing them in equation format will be effective and the same has been done below:

$$S_{A+} = \sum_{(u,v) \varepsilon A+} S_k(u, v)$$
$$S_{A-} = \sum_{(u,v) \varepsilon A-} S_k(u, v)$$

Step 3: Feature value of HLBP is evaluated with using below representation:

$$I(\text{HLBP})_{T,\ K,\ x,\ y,\ w,\ h,\ \theta,\ p}$$

$$(I) = \begin{cases} 1 \text{if } p.(S_{A+} - S_{A-}) > p._{\theta} \\ -1 \text{ if } p.(S_{A+} - S_{A-}) <= p._{\theta} \end{cases}$$

LBP code designed is observed to be strong to the illumination changes and parameter S_k will outperform with better and enhanced results compared with LBP:

Step 4: The final stage is to feed the third stage result, i.e., HLB feature descriptor to the LP boosting classifier (He and Wang, 1992; Jabal *et al*., 2013; Coggins and Jain, 1985; Fang *et al*., 2010, 2011). The classifier mentioned here, improves the classifications. The LP boost strong classifier pays attention on the weak classifier for mining the features based on Haar local binary pattern feature descriptors. Researcher Fang (2010, 2011) suggested usage of min-max theory for better classification with reduced misclassification. The major recompenses by LP boost classifiers are, it accomplishes train consecutively for the weaker classifiers.

METHODOLOGY

Having analyzed on the schema and the methods, the next stage of setting the test bed where the algorithm is ported has been done. A PC with Linux and OpenCV having been installed was suffice for the research work. OpenCV is open computer vision, which is one of the most frequently used packages for image processing applications. It is because of the available library files, versatility with respect to platforms and most importantly community support. Machine which had been used had Ubuntu installed, RAM of 4 GB, Intel CORE 2 DUO which can work up to 2.33 GHZ speed. The next major part in the research is the dataset. Here are the three data sets which have been used in the research. All three are highly notable and unique in nature because of the way they have been framed. VisTex, UMD and UIUC are the datasets considered.

Vision Texture database (VisTex): VisTex, the name is very famous among the image processing researchers. It is a very frequently used database which was framed by the Vision and Modelling team at the MIT. Images in this data set have been grouped based on their contents and orientations, which make the data set unique. It is also created by keeping a goal of handling the real time conditions and challenges. It has the mixture of traditional and non-traditional images. Different lighting conditions have been taken into consideration for framing this data set as daylight, artificial-florescent and artificial incandescent. The sample images from VisTex are presented in Fig. 3.

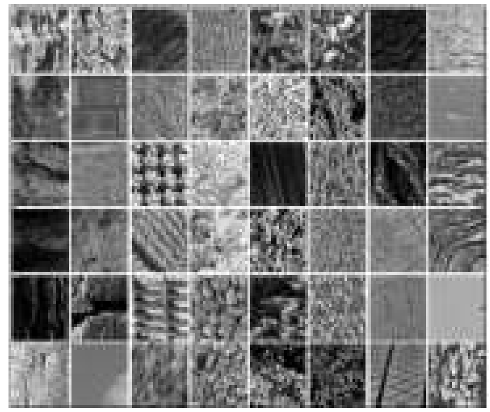

Fig. 3: VisTex dataset

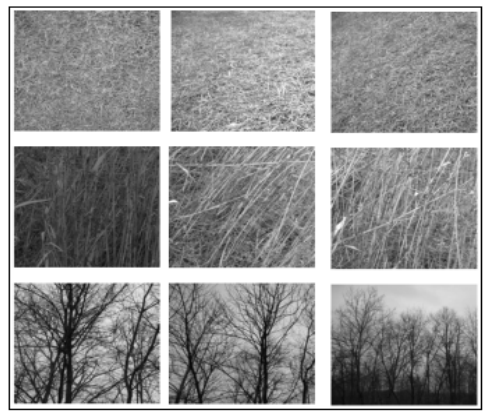

Fig. 4: UMD dataset

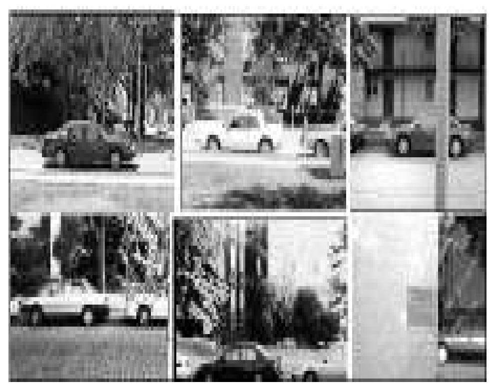

Fig. 5: UIUC dataset

UMD dataset (University of Maryland Dataset): University of Maryland dataset is a strict competitor for the VisTex dataset in terms of quality and content. And hence is the reason this data set has been preferred for our research. UMD texture incorporates noteworthy perspective changes and different scales. Furthermore, unrestrained illumination conditions are used for this dataset. Images including fruits, greeneries, textures of floor patterns and so on. The trial images from UMD dataset are illustrated in Fig. 4.

Table 1: Information on the datasets used

Data set	Color/gray	Number of images	Dimension of the images
VisTex	Color	150	512*786
UMD	Color	185	1280*900
UIUC	Gray	200	640*480

UIUC dataset: The UIUC dataset is highly noteworthy because of the way it has been framed. This dataset includes the surfaces which are based out of timber and sandstone, mat and blocks or mixture of both. Since the two data sets VisTex and UMD are very intense, this dataset has been included in the research as it skinny. The sample images from UIUC are offered underneath in Fig. 5.

A table has been composed below with summary of information about the datasets used. Table 1 can be referred for the same.

RESULT ANALYSIS

The results and the corresponding analysis have been done with all the three data sets and the same have been summarized in the below tabular columns Table 2 to 4. The proposed algorithm for classification has been compared with feature descriptor mean, LBP and HLBP. The graphs shown in Fig. 6 to 8, respectively are revealing the fact that HLBP feature vector improvises the results by a huge margin for scale and rotation invariants. One can refer to the charts for further understanding. The area of improvement in this research could be on the classification side where it can address multi class problems. Also the same can be ported to smaller computational engines as embedded boards.

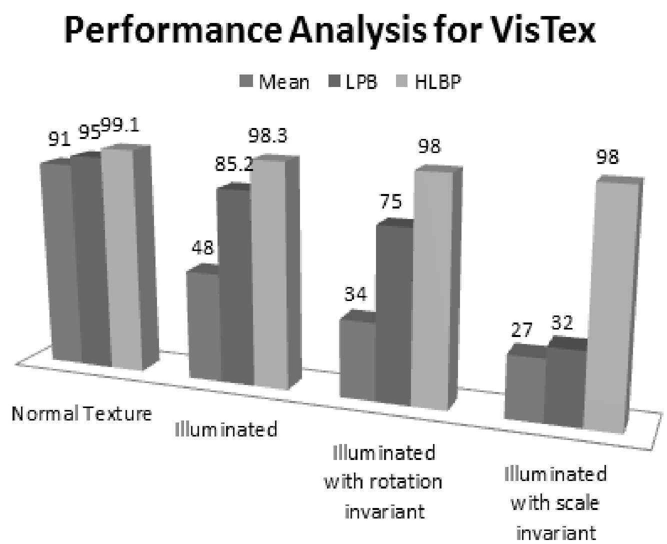

Fig. 6: Performance analysis for VisTex

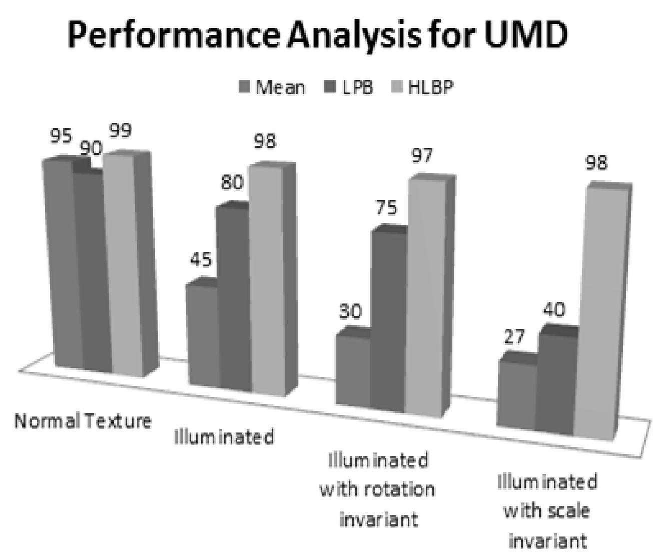

Fig. 7: Performance analysis for UMD

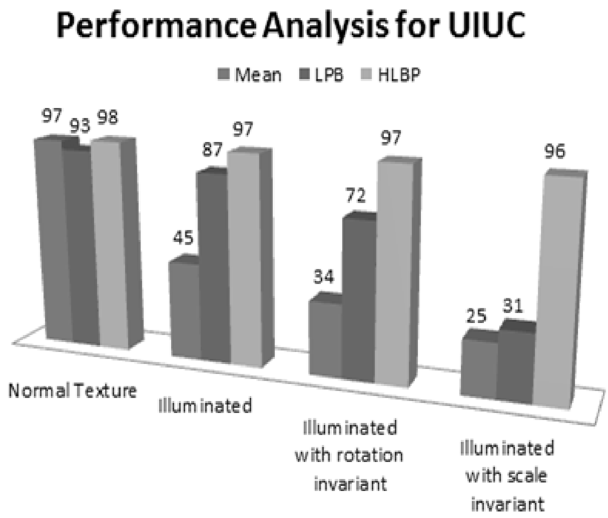

Fig. 8: Performance analysis for UIUC

Table 2: LP boosting classifier results (UMD data sets)

Feature descriptor	Performance (in %)	Remarks
Mean	50.00	Failed to survive in illuminative situations
LBP	71.80	Showed a reasonable resistance in illuminative conditions and failed in invariant conditions
HLBP	98.35	Showed excelled resistance in both illuminative and rotation scaled invariant conditions

Table 3: LP boosting classifier results (VisTex data sets)

Feature descriptor	Performance (in %)	Remarks
Mean	49.25	Failed to survive in illuminative situations
LBP	71.25	Showed a reasonable resistance in illuminative conditions and failed in invariant conditions
HLBP	98.00	Showed excelled resistance in both illuminative and rotation scaled invariant conditions

Table 4: LP boosting classifier results (UIUC data sets)

Feature descriptor	Performance (in %)	Remarks
Mean	50.25	Failed to survive in illuminative situations
LBP	70.75	Showed a reasonable resistance in illuminative conditions and failed in invariant conditions
HLBP	97.00	Showed excelled resistance in both illuminative and rotation scaled invariant conditions

CONCLUSION

In pattern classification, the rotation invariant texture method is implemented through the Haar local binary pattern method. Then, the corresponding pattern is extracted through the sequential histogram that based on rotation invariant parameters. The extracted patterns are manipulated for classification through the strong boosting classifier. It applied and tested with various standard datasets such as UMD dataset, VisTex dataset and UIUC dataset. The performance results shows HLBP on rotation invariant algorithm outperforms various existing methods. In future, this concept is exploited for many multidisciplinary fields that associated to texture classification of images.

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