REVIEW ON TEXTURE IMAGES CLASSIFICATION BY LBP APPROACHES

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Abstract

Texture classification is used in various pattern recognition applications that possess feature-liked appearance. This paper expects to incorporate the ongoing work on the use of feature extraction and classification methods. In this work review on various sort of LBP-based features classification techniques is carried out. LBP and its variations have been broadly utilized in several applications of different fields like PC vision, analysis of texture, recognition of pattern and so on. Here survey dependent on the investigation of Local Binary Pattern and its variations is provided. Most of the applications utilizing comprehensive new forms of feature descriptors have been talked about along with their upsides and downsides.

***Keywords*-Texture, Feature extraction, LBP, classification.**

I. INTRODUCTION

In general, texture plays a significant role in various applications of computer system. Most of the methods are used for analysis and description of textured surfaces. There are so many variations that occur in texture appearance mainly caused by transforming the conditions of image and illumination. The applications of real-world normally contributes in production of a large deal of complex data texture to quickly process and it must be effectively dealt in order to get explored and exploited [1]. An operator of local binary pattern (LBP) generally offers an effective and efficient method for analyzing the properties of textures. It involves an easy theory, which combines several structural properties and statistical analysis of textural methods. LBP represents an invariant that works against the monotonic form of gray-scaled variations and it involves several extensions in response to invariant rotation-based textural analysis. The real-world analysis of texture data is critically very time consuming a tiresome [2]. Usually, there occurs no such prior knowledge or other ground truth of data availability, and significant texture properties should be remembered from such kind of images. This represents a demanding task in the field of texture-based analysis.

1.1 Overview

The process of texture analysis is considered as major area in technology of computer vision and it contains more significant applications such as object-based detection, face recognition, filtering of image, content-based access, and segmentation to the databases of image [3] [5]. The classification of texture can be usually defined as a footprint for assigning a textural image into a set of previously defined subclasses or categories. Such a step needs to explain an efficient form of descriptors, which represents and discriminates distinct classes of textures. The LBP i.e. Local Binary Pattern is considered as the most fortunate statistical type of approach due to its robustness, potency against the changes done to intensity of illumination and the analogous fast computation [3] [4]. For the process of encoding LBP, each and every gray pixel is mostly compared with the surrounding neighbors and the analyzed results of such kind of comparisons are summed and weighted in order to provide a number in binary form. The textured features so obtained represent the local binary pattern-based histogram, whose values of bin count are mostly dependent over its neighbors' number. However, in most of the case when the neighboring pixels number usually increases, the dimensionality feature will exponentially increase. The texture operator on the basis of local binary pattern was firstly represented as an integral measure for the contrasting local type of image. The first operator embodiment worked with eight of the pixel neighbors by using the center pixel value as a threshold [4, 16]. A local binary operator code for its neighboring members was generally produced by the multiplication of the threshold values along with the given weights to the analogous pixels, and the summation of the result analysis as shown in figure 1.

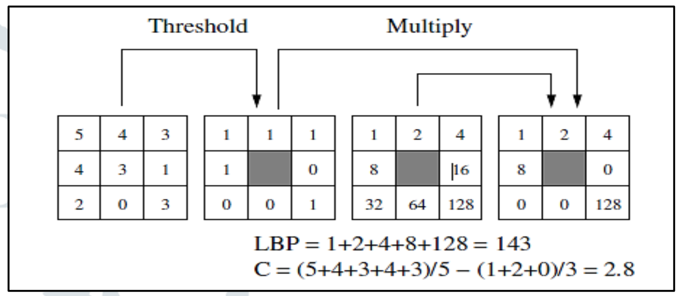


Figure 1: Calculation of contrast measure and LBP code

The present operator of LBP, as described, is somewhat distinct from its basic type of version: the real definition is generally enhanced to a number of extensions and an arbitrary form of circular neighborhoods has been proposed. The operator of the process is generally associated to most acclaimed methods of texture analysis.

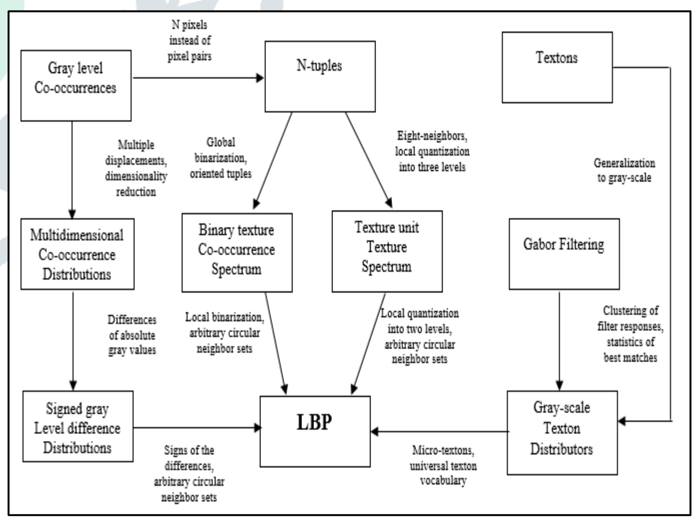


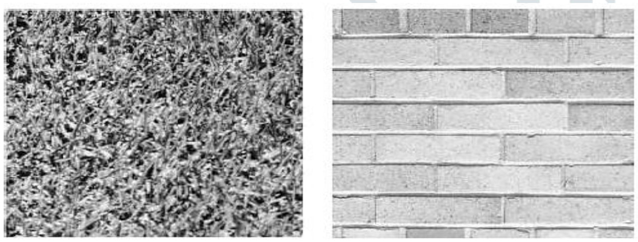
Figure 2: Texture analysis process based on LBP [16]

1.2 Texture and its distinctive properties

Texture analysis can be observed as a visual-based surface or material appearance of a surface. The textures usually appear in various types of environments and objects placed universally and they generally involve several distinct elements. Considering, for instance, the fingertip skin looks or the cloudy sky appearances. Both of the presented forms represent two distinct textured views in most of the aspects.

In case of fingertip, there are certain variations in its lining patterns and shape act as a biological form of marker for each and every individual, while in case of sky-based view, the properties and shapes of clouds designs a distant type covering the earth. The both above instances are considered as textures from distinct scales. The place or location of viewing mostly affects the texture appearance in large [5] [12]. Typically textures and its method of analysis are associated and are categorized into two of the major classes with distinct computing methods: the structural and the stochastic methods.

The textures of structural type are generally of artificial form with a continuous appearance involving, for instance, of square or line primitive type of patterns located on the surface in a systematic way like the brick walls [5] [22]. In case of analyzing structural texture, the property of textures and the textural appearance is generally explained with distinct rules that help in specifying different kinds of elements in the surface and how they usually are placed. The imaginary form of textures are basically natural and subset of textured elements that are randomly distributed, which can be again, for instance, curves or lines (e.g. bark of a tree). The experimental result of such kinds of textures is usually based on the properties (statistical) of regions and pixel image [6]. Figure. 3 represents a texture-based example from both the classes taken from popularly-known album i.e. Brodatz album (1966).



(a) (b)

Figure 3: Stochastic and structural textures [12] [13]

1.3 Textured features Characterization

In characterization of surface texture, the object surfaces are renowned as per some of the properties such as roughness. Additionally in case of visual-based separation, an acceptable description of surface-based appearance can be provided. Essentially, each of the surface contains a texture at some of its scale values, but characterization of surface is not bounded strictly to the analysis of texture [17]. Rapid growth in the methods of developing equipment and computer vision has upgraded the machine vision use in case of characterizing the surface. In natural vision, texture plays a key role and it has been applied widely to various problems of surface characterization . In the past years Haralick et al. (1973) applied a method of texture analysis to remote-sensing images for the purpose of doing terrain-based analysis. The experts generally tried to categorize the image regions to a set of predefined classes in order to form the sensed scene description. Gamba & Dell'Acqua (2003) helped in characterizing [17] the urban environments on the basis of residential-based density that was sensed from synthetic aperture radar (SAR) images using the textural information. . Oliver (2000) used the concept of texture analysis in order to classify the SAR image regions to forest and not-forest classes in determination of the rain forest state. The process of characterization of textured materials is usually very difficult and the main aim of characterization generally depends on application. Generally, the aim is to provide material-based analyzed description that can be used for the classification of result for a finite class's numbers or visual surfaces exposition [11] [14].

1.4 Texture Analysis

Traditionally the problems of texture analysis are classified into following four categories: texture segmentation, texture synthesis, texture classification, and the shape from texture. Critical machine vision-based issues are generally related to first two: segmentation and classification.

(a) Classification: Classification is considered as one of the main issue in machine vision and pattern recognition. The main objective is to classify the unknown type of objects into pre-defined classes or search the probability for each of given categories. In classification of texture, images are generally classified by authorizing the not known sampled images to predefined categories of texture categories as depicted in Figure. 4 below.

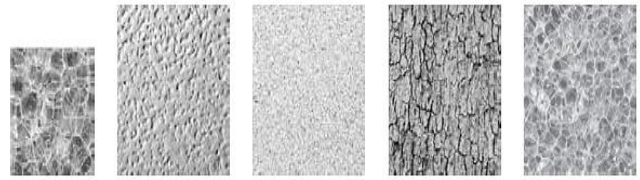


Figure 4: Texture classification example [16] [17]

(b) Segmentation: The goal of image segmentation is to partition the image into regions that represent meaningful objects or areas in the image. The segmented regions should have uniform and homogenous properties with respect to some characteristics such as color or texture. The regions that are placed adjacent must differ from their neighbors on the basis of the above mentioned properties. Most of the times, it might be very hard to determine the distinct region boundaries.

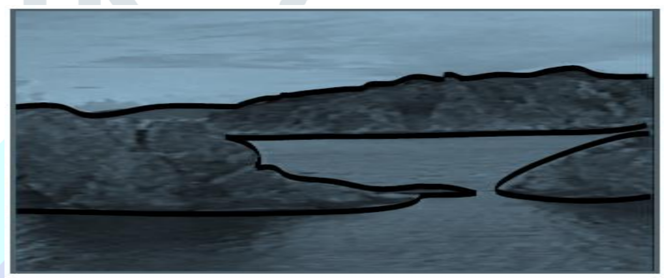
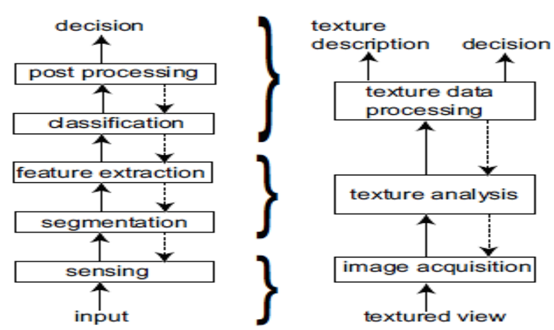


Figure 5: Texture segmentation example [17]

Figure.5 shows an example of a natural scene image segmented into regions of homogenous texture manually.

1.5 Designing Texture Characteristics

The human-based visual system generally consists of description of sensed textural scene, but many of the problems takes place in its computational analysis [7] [9]. The machine-based vision on the basis of textural characterization is usually considered as the pattern for recognizing certain issues where the major aim is to provide a description of data sensed or to make some of the selective decisions based on it. Figure.6 (a) depicts the block diagram of an exemplary pattern-based recognition system presented by Duda et al. (2001). Figure.6 (b) depicts an example of comparable system of texture-based characterization.



(a) (b)

Figure.6: Pattern-based recognition system

The process of texture characterization can be generally thought of as the task of pattern-based recognition (Figure 6(a)) and a simplified form (Figure 6(b)).

(a) Texture-based feature extraction: While the development of texture-based measures, one of the major issue that is to be known is to carry out invariant type of properties in texture features.

1. Statistical-based texture features: Obtained by calculation of several statistical-based properties, such as variance and mean from the image-based gray level histogram. The first-order statistics performance is usually very poor. Simple form of textural statistic is the calculation of autocorrelation-based image function. Such a process can be used for assessing the coarseness as well as the regularity of the texture that is present in the processed image [13].

2. Geometrical and Structural texture features: Geometrical and structural features are generally more stable and reliable in the overall illumination-based transformation rather than the statistical-based features, but these are really powerfully over the detection on primitive basis. The structural methods are more often well justified with the help of psychophysical-based studies of perceiving the textures: a human could distinguish the textures with distinct elements of textons.

3. Model-based texture features: The methods of Model based texture features rely over the image-based model that is generally used for describing the texture with an approach of parametric type.

4. Signal-processing based texture features: Such an analysis approach usually filters the image with unique kind of filters and helps in utilizing the responses of the filter in order to design texture features.

5. Texton statistics and local texture features: A texton usually involves small number of image bases with spatial deformable configurations. The Local Binary Pattern (LBP) represents a method used for describing surface-based textural characteristics. The results of the implementation process of LBP rely on two type of texture. One is natural and the other is the unnatural textures that basically show that the extracted textural feature can be used in the form of input for the classification of pattern.

(b) Local Binary Pattern and its extensions

Figure.7 indicates how the practical local binary pattern (LBP) is computed. In an image, for each of the pixel, the thresholding property of neighborhood helps in production of a binary code (8 pixels) along with the center-pixel value. The process results in formation of histogram modelled for collection of distinct binary patterns occurrences presenting distinct kinds of curved spots, flat areas, edges, etc. The gray levels average below the center-pixel value is usually subtracted from the gray levels above or nearly equal to the pixel center [8] [10]. The local contrasting measures and two-dimensional (2D) LBP distributions are calculated from the whole image or the region of image, which are further used as the LBP/C features as discussed below. The contrast measure is usually more sensitive of the lighting conditions, which should be taken into account when using this feature. The real LBP operator based 8-bit version helps in considering eight of the closest neighbors only for each of the pixel and it is generally of rotational variant, but invariant to monotonic changes in gray-scale. The LBP based dimensionality of distribution can be evaluated in response to the used number or count of neighbors [12]. The basic version of LBP (8-bit) is able to present around 28 distinct local type of patterns, so the feature-vector based dimensionality obtained is 256.

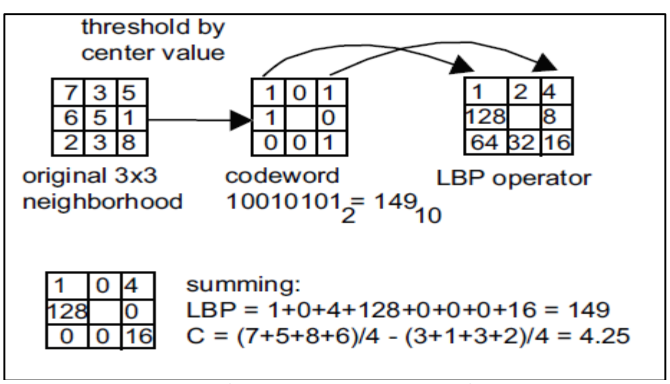


Figure.7: Computation of LBP and local contrasting features [17]

In Figure.8, the inspiration and the circular idea behind the local binary pattern multiresolution form was depicted. The center pixel-based neighborhood is taken to be in circular form, and any kind of neighbor samples number (= P) can be chosen from perimeter (circular) at any of the scale (= R). Neighboring samples are generally interpolated on the presented circle with equal spacing.

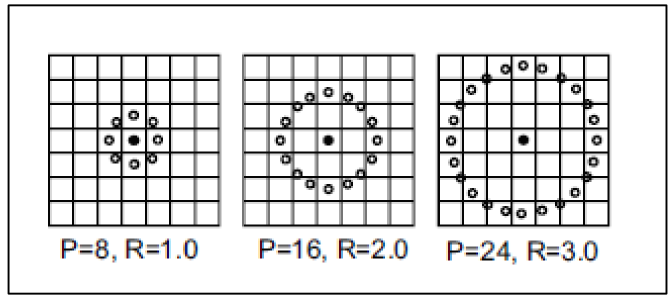


Figure 8: Circular neighborhood of pixel in multiresolution LBP.

In the multiresolution model of the LBP, separate operators at different scales are first constructed and the final feature vector is a combination of individual feature vectors created simply by concatenating them one after another [5] [13]. Combining different operators can also be done by construction of joint distribution of all distinct type of LBP codes, yet such kind of distribution gets too large and is considered to be sparse in practical cases.

II. RELATED WORK

Xiuquan Wu, et.al [1] proposed an effective and novel strategy i.e. central pixel selection (CPS) by using a gradient type of information in order to classify the texture image central type of pixels into distinct classes on the basis of gray-value local distribution. The experts further introduced this strategy into a local binary pattern (LBP) framework and assigned an adaptive form of sampling radius for each of the central pixel in regard to its class from where it belongs. The experiments were based on five of the texture-representative database such as CUReT, UMD Outex, A LOT, and UIUC helps in validating the efficiency of the system proposed on the basis of CPS strategy, that could possibly achieve around 16% of the improvement over real LBP and an improvement of 1%–10% as compared to best accurate classification among other LBP benchmarked variants. Davood Gharavian, et.al [2] proposed a novel method for classification and analysis of textures on the basis of a specific combination of Fourier transforms, ridge let, and wavelet along with mechanism of support vector machine. The proposed method was evaluated for 13 textural datasets that were obtained by three of the real type of datasets that contained 111 and 25 textures from a database named Brodatz and 24 type of real textures from a database name OUTEX. The simulation results demonstrated the efficiency, stability, and capability of the method proposed specifically for the noise-resistant and real time invariant texture classification and analysis. Swalpa Kumar Roy, et.al [3] proposed a novel kind of Fractal Weighted Local Binary Pattern texture descriptor, popularly known as FWLBP. The fractal dimension (FD) represents the measure i.e. invariant relatively to the scaled changes, and represents well correlation with human-based viewpoint in context of roughness of surface. The framework proposed descriptor was of scale invariant form, and was also robust in both reflection and rotation, and tolerant partially to illumination and noise changes. Qiqi Kou, et.al [4] focused on enhancing the property of robustness to viewpoint, scale, and a wide number of trained samples, multiresolution and multiscale was explored by diversification of two of the parameters. . However, a cross-scaled joint feature based representation took place on complementary generated binary responses that resulted in the proposed concave-convex local binary pattern i.e. CCLBP, which captured a discriminative information with low system dimensionality. The experimental analysis results on the basis of three standardized form of texture databases demonstrated that framework proposed CCLBP achieved an impressive performance or outperforms the existing state-of-the-art.

Jing-Ming Guo, et.al [5] studied an individual or joint histogram that can be obtained from local binary pattern code that was basically used as a feature of descriptor in some of the applications. However, the LBP feature was not good candidate for capturing the information of the color image that made it less suitable for similarity measurement of colored images with its rich color-based information. . As presented in the result analysis, the hybrid forms of CIF and LBP feature presented a satisfied result and it outperforms the existing state-of-art methods over certain databases of image. Thus it forms a competitive method or candidate in classification and retrieval application. Dr. Maitreyee Dutta, et.al [6] overviewed the Local Binary Patterns (LBPs) that were used firstly for describing the ordinary textures and as the face was seen as micro-texture composition depending upon the situation (locally), it was also useful for the purpose of face description.

The descriptor of LBP generally consists of overall local texture and global texture representation that was evaluated by image divided into certain blocks and further computing the histogram of texture for each of the texture. The results were further concatenated in a general form of descriptor vector that would be later used for feeding an adequate form of classifier for deciding the input image based face likeness or the input face identity for face recognition. Esa Prakasa [7] presented the Local Binary Pattern (LBP) that represents a method used for describing the surface with textural characteristics. By implementing the process of local binary pattern (LBP), the probability of pattern-based texture can be briefly summed into a method given by histogram. The values of LBP was required to be found for the overall pixels of the image. The LBP experimental results were based on two of the texture types; one was the natural texture and the other one was the synthetic texture. It has shown that the extracted form of textural features can be used as the input for the purpose of classification of patterns. Songyang Lao, et.al [8] considered the Local binary patterns (LBPs) as the most computational efficient highly-performance-based textural features. However, the method of LBP was conscious to noise of image and was not capable to capture the information about the macro-structure of the system. In order to properly address such drawbacks of the system, the researchers introduced a novel type of descriptor for the purpose of classification of textures, the robust form of MRELBP i.e. median robust extended LBP. An overall evaluation of benchmarked set of data reveals the high performance of MRELBP that was robust to the variations of gray scale, noise and rotational changes. MRELBP produced best level of classification of about 99.38%, 99.82%, and 99.82% on three of the popular suites. Wei Li, et.al [9] focused on the paradigm classification for exploitation of heathy textural HIS-based information. The framework proposed usually employed local binary patterns (LBPs) to extract local features of image features like corners, spots, and edges. The two basic levels of fusion i.e. decision-level fusion and feature-level fusion were applied to the extracted form of LBP features with the Gabor global features and real spectral type of features. Here, in case of feature-level fusion, the process consists of multiple features concatenation prior to classification of patterns, whereas in case of decision-level fusion, the process depends on the probability-outputs of each single pipeline classification and the fusion of soft-decision rule is generally adopted to sum up the results from ensemble classifier.

Table.1 Existing LBP based Feature Extraction Models

Author's Name	Year	Methodology Used	Proposed Work
Marko Heikkila, et.al	2006	Adaptive form of Local Binary Pattern (LBP) Histograms	Presented an efficient novel texture-based approach for modelling the background of the framework and detection of the objects moving from a video-based sequence.
Lei Zhang, et.al	2010	Local Difference Sign-Magnitude Transform (LDSMT)	Proposed a complete design of LBP operator along with a CLBP scheme that form a completely associated form of LBP for the purpose of classification of texture. A region (local) was presented by a LDSMT i.e. local difference sign-magnitude transform (LDSMT) and the pixel center.
Wei Li, et.al	2015	LBP features with the Gabor Global Features And Real Spectral Type of features.	Focused on the paradigm classification for exploitation of heathy textural HIS-based information.
Songyang Lao, et.al	2016	MRELBP i.e. Median Robust Extended LBP	Considered the Local binary patterns (LBPs) as the most computational efficient highly-performance-based textural features
Dr. Maitreyee Dutta, et.al	2016	Local Texture And Global Texture Representation	Overviewed the Local Binary Patterns (LBPs) that were used firstly for describing the ordinary textures and as the face was seen as micro-texture composition depending upon the situation (locally), it was also useful for the purpose of face description.

Ghulam Muhammad [10] proposed a novel system for automatic classification of distinct types of dates from the given images. All the dates have certain distinguishing features which are helpful in recognizing a specific date. The features involves texture, shape, and color. In this framework, a coloured dated image gets decomposed into the components of color. Further, description of local texture was considered as Weber local descriptor (WLD) or local binary pattern (LBP). The shape and size were affixed to descriptor of texture for full date description. The support vector machines were used as a classifier and the system proposed achieved an accuracy of about 98% for classifying the description of date. Lei Zhang, et.al [11] proposed a complete design of LBP operator along with a CLBP scheme that form a completely associated form of LBP for the purpose of classification of texture. A region (local) was presented by a LDSMT i.e. local difference sign-magnitude transform (LDSMT) and the pixel center. In the proposed framework, the center pixels generally represent the gray level image and these are transformed into binary-code, specifically named as CLBP-Centre (CLBP_C) with the help of global thresholding process. LDSMT disintegrate the local differences of image into two of its complementary type of components: magnitudes and signs, and two of the operators i.e. CLBP-Magnitude (CLBP_M) and CLBP-Sign (CLBP_S) are proposed for coding them. Guoying Zhao et.al [12] overviewed the dynamic texture which represented the textural extension to temporal domain. Recognition and description of dynamic form of textures have influenced a boosting attention. The experts have proposed a novel method for dynamic feature recognition along with its extensions and simplifications for analysis of facial image analysis. . A block-based approach was also proposed for dealing with events that were specific dynamically such as the facial expressions, where the spatial locations and local data information were also taken into account for its working operation. The two dynamic databases of textures such as MIT and DynTex, outperformed the already existing state-of-art. The block-based approach was calculated with the help of a database, namely Cohn-Kanade facial expression database providing impressive results. Marko Heikkila, et.al [14] presented an efficient novel texture-based approach for modelling the background of the framework and detection of the objects moving from a video-based sequence. Each of the pixel was modelled as a combinational group of adaptive form of local binary pattern (LBP) histograms that were

evaluated over a circular-based region surrounding the pixel. The approach generally provides lots of advantages as compared to existing systems.

III. CONCLUSION.

Pattern recognition applications use various texture classification techniques which in turns uses various feature extraction methods. Local binary pattern is one of them. In this paper, LBP and its variants over the recent years are analyzed. It includes LBP, CCLBP, MRELBP and their hybrid forms. The analyzed work is presented in the form of a table containing name of authors, years of publication and their proposed ideas and methodologies used to enhance the feature extraction techniques. From the analysis of literature, it is discovered that no single descriptor has been created which covers each one of the confinements. Consequently, there occurs a necessity of another powerful texture-based descriptor that defeats the gaps and holds the upsides of testified descriptors.

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