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Research Article

Robust Image Feature Description, Matching And Applications: A Review

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Abstract

Many computer vision applications such as visual communication and image processing, object detection, shape recognition, recognition of face and face expression, 3D reconstruction, etc. included two images to suit. To compare two images, or in other words, to evaluate the similarity / difference between the two images, a certain picture definition is required since the comparison between the raw intensity values of two images takes more time and is influenced by small differences in the inherent properties of each image, such as luminosity, orientation, scaling etc. The photographs may then be corresponded with their definition extracted from the fundamental characteristics of the picture, such as colour, texture, structure, etc. The actual descriptor / signature of the picture is this definition. Any descriptor's main objectives are (1) to collect discriminatory picture details, (2) to provide the invariance to geometric and photometric modifications, and (3) to - its size. The key objective of the paper is to construct the image descriptors with differential strength, image variations robustness and small scale. For regionally based photos under different geometric and photometric transformation conditions we have provided an interlaced strength value local descriptor (IOLD). We have checked four local gray-scale image descriptors, namely Local Extremity Diagonal (LDEP), a Local Bit plane Diagonal (LBDP) pattern, local LBDISP and local wavelength (LWP) pattern in the MRI and CT repositories for biomedical image retrieval. Four colour-based local descriptors, i.e. local colour occurrence descriptors (LCOD), robust hybrid (RSHD) scale and rotating, multiple-channel adder based, and multi-channel decoder-based, local binary (md LBP) patterns for natural and texture image recovery, have been reported. For more details, see LCOD. As a favored phase in pre-processing an illumination compensation mechanism was recorded. Filter bags and SVD-based solutions were suggested in order to boost descriptor efficiency.

Keywords: Descriptor, colour, texture, shape, Recognition, classification

1. Introduction

Human beings perceive their environment through audio, visuals, heat, smell, touch, etc. and react accordingly. Out of these media, the visual system is the key component of the human brain to collect most of their environmental information. The computer vision is also dedicated to design the artificial systems to sense and realize the surroundings. descriptors came into existence and later on, the images are being matched using the descriptors [1-5].

The characteristics of the details contained in the photographs are in the machine visual field, picture descriptors or graphic descriptors. The basic characters including motion, sound, colour and type are defined. In the midst of chaotic and multiple geometrical and photometric transformations, a descriptor must be extremely recognizable to separate one category of object from another category of object. [1]. For last few decades, a rapid growth is observed in the amount of visual content in digital form due to the highly and diversified uses of the internet and new technologies. In order to index, retrieve and categorize the multimedia content efficiently and accurately, it is extremely important to investigate the systems which characterize the multimedia information as per the application requirement. The appearance based image descriptors are actually the key medium which represent the information carried by any image/region/object and allow the effective and accurate decision making. Diagram. 1.1 demonstrates the descriptor formulation that can be summarized as: a) remove the picture characteristics as small areas, b) define and field through the feature descriptors and c) using descriptors to compare, practice, identify, etc. There are three questions to address to the key problems related to creation of successful image descriptors [5]: a) Where to measure the descriptors? b) How will the descriptors be calculated? And c) How will the descriptors be compared?

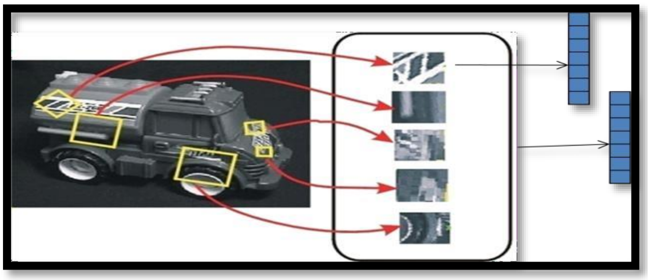


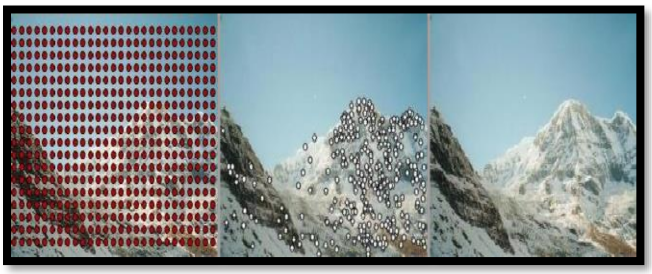
Fig. 1.1. Descriptor construction from a picture area of interest [5].

1.1 Where will the descriptors be computed?

The descriptors can be calculated by using 3 methods, Grid [6-8], [9-15] and Global [16-27]. The descriptors can also be derived from each region of interest. Image. 1.2 presents map, key point and regional method for function identification. In the grid solution, the picture is split by the rectangular grid in several regions with each row reflecting an area. The descriptor is measured separately across each picture map. Any interesting points will be pictured in the key-point method and the descriptors are measured in the vicinity of every point of interest. The picture itself is viewed in a global context as the same area, and there is a descriptor. The grid- and key-point region-based descriptors are generally high because both measures the descriptors for several picture regions; but the global region-based descriptor parameter is generally low when a single descriptor is measured. Local region-based descriptors for large image repositories are typically used.

1.2 "How to Compute the Descriptors"?

There are different ways to measure a descriptor. The architecture of the descriptor depends entirely on the program and demand. Various requirements need specific invariances, so specific descriptors are needed. The pictures in Fig, for examples. 1.3 are identical if only the shape of the picture is taken into account; but, they are distinct if one takes into consideration the color distribution of the picture.



(a) **(b)** **(c)**

Fig. 1.2. "Extracting regions using (a) Grid, (b) Key-points, and (c) Global approach" [5]

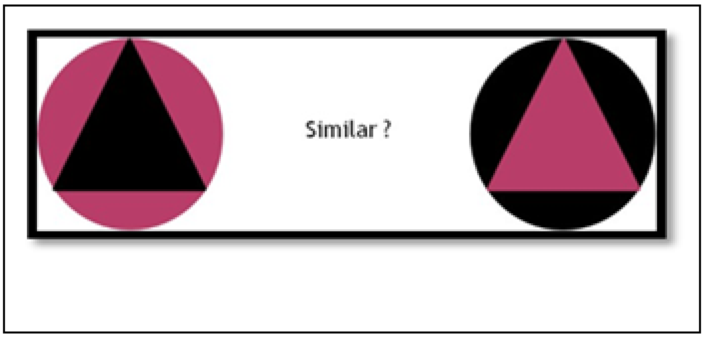


Fig. 1.3 Similarity relies on the criteria for implementation

The main features of most photographs and also the basic styles of features for representing the picture are color, form and shape [24]. Color is the fundamental quality of the visual information. The simple color characteristics are RGB histogram, adversary histogram, histogram Hue, rg histogram, converted color view, color moments, color moment invariants, etc. In order to define the picture regions or textures, the texture is an essential characteristic of an image. The mean, variance, capacity, correlation, entropy, comparison, homogeneity, cluster shadow, etc. are contained in this area essentially [29]. The type representation plays a significant role for the semantic explanation of the meaning of an image. The relevant image-based form-descriptor descriptors are Fourier descriptors, space-scale descriptors, angular radial transform, image moments, etc. [30]. For different applications, multiple descriptors are introduced utilizing different color, texture and form characteristics combinations. Some descriptors for different applications mentioned in the remaining articles are also examined in this article.

1.3“How to Compare the Descriptors”?

Image descriptors and their distance calculations for the descriptors are usually given. In literature which measures the dissimilarity of representations, the most common distance metric used is the Euclidean distance. Unless the difference from the Euclidean between the two descriptors is greater, then two descriptors are more common; the pictures are identical [31]. Many regular distances are L1, Distance to Earth Movers (Emd), Cosine, Canberra, D1, and Chi-square. Most typical distances are 32-35. The basic function of determining resemblance is to determine the variations between the two picture descriptors. Let the descriptors of Ma and Mb be classified as Ha (1), Ha (1), Ha(2) and Ha (dim), ..., Ha (dim) and Hb = Hb (1), Hb (1), Hb (2), Hb (1) and Hb (2), ..., Hb (dim)} respectively. The varying lengths are as follows:

Euclidean distance

$$Euclident\ (D^a, D^b) = (\sum_{k=1}^{dim} D^b(k) - D^a(k)^2)^{1/2}$$

L1 Distance

$$L_1\ (D^a, D^b) = \sum_{k=1}^{dim} |D^b(k) - D^a(k)|$$

Cosine distance

$$Cosine\ (D^a, D^b) = \frac{(\sum_{k=1}^{dim} D^b(k) * D^a(k)^2)^{1/2}}{(\sum_{k=1}^{dim} D^b(k)^2)^{1/2} * (\sum_{k=1}^{dim} D^a(k)^2)^{1/2}}$$

EMD Distance

$$Emd\ (D^a, D^b) = \sum_{k=1}^{dim} |cdf(D^b(k)) - cdf(D^a(k))|$$

Canberra distance

$$Canberra\ (D^a, D^b) = \sum_{k=1}^{dim} \frac{|D^b(k) - D^a(k)|}{|D^b(k) + D^a(k)|}$$

The Di distance

$$di\ (D^a, D^b) = \sum_{k=1}^{dim} \left| \frac{D^b(k) - D^a(k)}{1 + D^b(k) + D^a(k)} \right|$$

Chi-square Distance

$$chisq\ (D^a, D^b) = \frac{1}{2} \sum_{k=1}^{dim} \left| \frac{(D^b(k) - D^a(k))^2}{D^b(k) + D^a(k)} \right|$$

Average retrieval precision (ARP):

$$ARP = \frac{1}{N} \sum_{i=1}^{N} P(X_i)$$

$$P(X_i) = \frac{I_n}{I_t} * 100$$

Average retrieval rate (ARR):

$$ARR = \frac{1}{N} \sum_{i=1}^{N} R(X_i)$$

$$R(X_i) = \frac{I_r}{I_{db}} * 100$$

Average retrieval accuracy (ARA):

$ARA = \frac{1}{N} \sum_{i=1}^{N} A(X_i)$,

Where A(X_i) is the accuracy for query image X_i and define as:

$$A(X_i) = \begin{cases} 100\ , where\ Ir\ is\ in\ majority\ among\ It \\ 0\ , \qquad else \end{cases}$$

1.4 Objective of the Paper

The objective of this paper is given as follows, which mainly covers the distinctive, robust and low dimensional image descriptors for computer vision problems:

- To construct the distinctive descriptors for computer vision application problem.
- To construct the robust descriptors against scaling, rotation, illumination, blur, compression, and viewpoint variations.
- To construct the low dimensional descriptors to minimize the matching time.
- To construct the multichannel descriptors for color natural and texture image retrieval.

2. Literature Review

This paper presents an extensive literature survey of image feature descriptors in many application areas of the computer vision. We organized this paper in the following manner: we reviewed the region-based local descriptors mainly with gradient distribution and order property in Section 2.1; we reviewed the local gray scale descriptors in Section 2.2 primarily for the biomedical images; we surveyed the local color descriptors for natural and textural images in Section 2.3; we also surveyed the brightness robust local descriptors in Section 2.4; we reviewed the pre and post processing approaches for boosting the local descriptors in Section 2.5; we listed the research gaps identified from the literature survey and future scope has been listed and finally, we summarized this paper in conclusion.

2.1Region Based Local Descriptor

Computer vision investigators studied extensively local characteristic descriptors developed over the observed areas of interest. Local features have been used in recent years in various visual application issues, including 3D reconstruction, panoramic sewing, and description of objects, image detection, and facial expression recognition and gesture function [32-45]. While defining local image functionality, the main focus is on optimizing the characteristics and making image transformations stable. The basic goal is first to define the affine invariant regions of importance and then the extract sequence descriptor in each of them. Detectors for the detection of focus areas of hessian-affine and Harris – Affine [46-47] were commonly employed. Once the area of interest is found, function descriptors are designed to enable the matching of the location. In the literature several practical descriptors with an increasing interest in region detectors [48] are suggested. In some distributions, the efficiency of picture descriptor centered on the spin map, the shape and controllable filters was found to be significantly better than those descriptors [49-51]. The gradient distributions are commonly used by distributional processes. For examples, the SIFT descriptor computes a histogram of 4 to 4 gradient orientation cells [9]. The popularity of the SIFT descriptor has inspired many other local picture characteristics such as SIFT-like descriptors such as GLOH, SURF and DAISY [52-55]. Recent works provide Gaussian types as a descriptor [56], a descriptor for picture blurred recognition applications [57], which utilizes alternate Hough and inverted Hough to generate robust compatible features [57]. Although invariant descriptor characteristics (i.e. RIFT and spin image [50]) do occur technically, they also disregard spatial information and become less distinctive. While rotationally invariant, theory is not consistently descriptive. For the picture feature descriptor Kim et al. [14], identical instructions have been used. The exact global and local orders to produce the EOD descriptor is merged. In order to describe the picture regions [59], orthogonal LPBs are combined with color detail While distribution-based descriptors are partially or entirely robust to several geometrical image transformations such as rotation, size, occlusions etc. Some researchers have suggested to analyze local intensity ranges rather than raw intensity values to alleviate this issue, since the invariance of monotonous variations is obtained by implementing the intensity value order.

OSID, LBP, LBP, CS-LBP, HRI, CS-LTP and LIOP [11-12, 16-17, 60-62 and 160-62] are popular order-based descriptors. Based on the ordering information [62], a local binary pattern (LBP) generates the template for each Pixel. LBP gains primarily from versatility of computation as well as from the invariance of lighting shifts, however LBP has some inconveniences, such as high-dimensional object computing and Gaussian noise avoidance in flat regions. A standardized LBP is suggested in [16], noting that the LBP sub-set comprises the majority of textural details. When contrasting only the center-symmetrical pixel size differentials, the CS-LBP rising LBP parameter [17]. Enabled by the CS-LTP descriptor, diagonal relations are called between the neighboring points [11]. Complementary information is provided for HRI and CS-LTP and combined in order to create a consistent description for HRI-CSLTP [11]. Wang et al. [12] recently proposed a Limited Intensity Patch Descriptor from a certain pixel to represent the neighboring intensity direction. We gave each neighbor a specific order and divided the whole patch in different areas by the global order of each pixel in the patch, determined the LIOP for each field, and averaged it to produce a single model. The main problem with LIOP is the assumption that its size decreases steadily and the amount of adjacent pixels is diminished. In different imaging environments, LIOP has used just 4 neighbors and shown very good performance but not more than 4 neighbors have been checked by its own inventors.

2.2 Local Gray Scale Descriptors

Photos play a significant part in data collection, identification of illnesses and research in the area of medicine. Medical imaging instruments such as computed tomography (CT), magnetic resonance imaging (MRI), and visual, radioactive scanning, etc., are also generating various forms of photographs to record the body parts 'features [63]. Such photos are used as a diagnostic assistance source. However, as the number of medical pictures increases rapidly every day, the identification of patients in medical institutions and clinics is becoming more complicated and requires more precise and effective methods for scanning and indexes photographs. In order to combat this issue on the basis of digital image content [54] such as color, cloth, form, and layout, photographs are continuously being replicated and recovered based on the content. In [36, 65] the Comprehensive Content-Based Photo Recovery Literature Review (CBIR) is provided.

The most important application of medical imaging equipment is the doctors who are specialists in recognizing the condition in the image by choosing the most appropriate pictures from the relevant comparison pictures. Different researchers report a variety of medical image retrieval schemes in the literature published [66-72]. Centered on the therapeutic effects, Muller et al. analyzed the medical solutions to CBIR [73]. -- image extracts the function vectors to promote the image search and contrasts the feature vector for the sample image with the database model function vectors. Any CBIR device is heavily dependent on its success and capacity. In recent retrieval and classification procedures, feature vectors are supplied utilizing picture visual details including shape [74-75], texture [32-33], boundaries [34, 76], color histograms [77-78], etc.

In the field of pattern recognition, texture-based image descriptors were commonly used for collecting fine picture data. A local binary pattern (LBP) for texture rankings was introduced by Ojala et al. [62]. Due to its reduced code sophistication and increased performance, LBP operators became more common in a range of applications like facial recognition [79], face paralysis analysis [80], pulmonary Emphysema analysis [81], etc. In view of the LBP's great success, several other LBP variants [16-20, 82-84] have suggested texture representation. A research is underway for the purpose of reducing the LBP dimension for local area compatible center symmetries (CSLBP) [17]. The generalization of LBP for facial recognition in different lighting conditions is implemented by Local Ternary Pattern (LTP) [18]. In fact, these approaches are invariant in lighting. Based on the uniformity of the pattern and brightness of the image, Peng et al. extracted texture clues in chest CT images [85]. We explained the shape and luminosity of the picture with prolonged rotations, local binary pattern and gradient orientation variations. Area of significance recovery in brain MR images on the base of the local structure in the picture is proposed by Unay et al. [37]. In the wireless capsule endoscopy photos, the SVM-based functional collection shall apply to the tumor recognition textural features [86]. For the characterization of CBIR tissues, Felipe et al. have used the co-occurrence gradient texture characteristic [87]. Cai et al. ([88] for positron emission tomography (PET) model recruitment was faced with a physiologic kinetic attribute to reduce the memory needed for image storage. Some methods planned for the recovery of medical images utilizing distance measurements and comparison are shown in [89-91]. Several researchers in medical CBIR systems [92-93] often present wavelet-based functionality. The methods used specifically for the transfer of the wavelet over images worldwide [94] (that is, 2-D image transfer).

The local function descriptors provided in the reported literature used a cited pixel's connection to the surrounding pixel [16, 18, and 32]. Such methods have also been used to some degree to exploit the interaction between adjacent pixels with efficiency, albeit at the cost of their high dimensionality.

2.3 Color Image Descriptors

The efficiency of any imaging system depends heavily on the corresponding picture quality descriptors [36]. The basic characteristics to characterize a picture are color, texture, form, gradient, etc. [36]. In the research community, the picture descriptor based on color and texture is very general. For object and scene identification in [28] a consistency assessment of image descriptors such as SIFT light, SIFT adversary, etc. is performed. Such descriptors first locate the regions in the picture with area detectors, instead measure the descriptor for each area and finally construct the descriptor using a word bag model. Therefore, researchers are trying to develop the word bag model [95]. GIST, which essentially is a comprehensive description and has acquired broader ads due to its high discriminatory ability, is another important descriptor [96-98]. Previously, descriptors based on local trends were used to characterize the picture function [1, 16-19, 45, 79, 84, 99-101]. These solutions are used mostly for gray pictures, that is, only on one screen, but most of the time natural color images with more than one channel have to be described in specific scenarios.

2.4 Brightness Robust Image Descriptors

The bottleneck in the past two decades has been lighting reliable picture matching and retrieval. Various methods were used in the published literature to address the problem of image retrieval [102-114]. The classification is primarily based on low-level characteristics including color, texture, shape, sketches, etc. Color is an important visual indicator to differentiate between the two images. Due to its simplicity and invariance, Color is a commonly employed low level function in CBIR systems. This role for image recovery and classification is improved by the sizes and rotation invariance properties of color hectographs. A color encoding that represents the frequency of the individual colors in the image is the simplest color encoding [115]. Color Coherence Vector (CCV) [116] and the Color Variations histo graph (CDH) [102] are some other light-based function descriptors.

For each color and edge orientation CCV codes color details into the embedded areas, while CDH describes the picture using a two pixel color differential in the map. Color details are also coded in the form of histograms recently collected via a Harris-Laplace multi-scale detector [117) over the local feature regions (LFs). The text urination function is important and commonly used for portraying images visual information. Recently, Shi et al. [118] implemented Square Symmetric Local Binary Pattern (SSLBP). The CLBP is used to diagnose Apple's disease [119]. The texture-inner pixel (BIC) classification (120) and the Structure feature histogram (SEH) [24] are adopted as texture-retrieval characteristics. The picture textures are also used for Angular information [121-122]. Angular information. Wang et al. for CBIR [123] incorporate color and texture characteristics. Descriptors focused on form and skeleton are also used as symbols to reflect the features of the body and have shown interesting results for identity recovery [124-126]. Shahabi and Safar [124] conduct a study on shape-based rehabilitation strategies. Saavedra and Bustos have used the idea of local key forms to encrypt entity shapes for sketch-based image retrieval as an alternative to local key points [125]. In addition, shape recovery is included in the synthesis of the sketches for both structure and sketching information [126]. Descriptors based on form and sketch typically require edge detection and picture segmentation that restrict their applicability. Four-strip matrix quantization [127], spatial relations [128], improvement of similarities [129] and short- and long-term learning fusion [130] are other retrieval methods. The descriptive function of the smaller level shows the picture details effectively and is used in many image problems combined, however, such characteristics do not produce better results and are prone to light variations (e.g. photometric transformations).

Any solutions to the issue of illumination sensitivity have also been documented in the published literature. The usage of a contrast stretching feature (i.e. contrast signatures) [131] is recorded for the recent detection of image focus points. In [132] the bi-log transition is used to eliminate the effect of lighting variation; this technique, though, requires to split the intensity value into lighting and reflectance portion. Several approaches for illumination reliable face detection have also proposed [133, 134]. Logarithm Gradient Histogram (LGH) is proposed for facial identification under differing illuminations utilizing the spectral range, magnitude and orientation of lighting [133]. In 134 [134], variations in illumination in a logarithmic context are balanced and transformed by truncating low frequency DCT coefficients using a discrete cosine transform (DCT). Nonetheless, this technique involves a parameter tuning to truncate the amount of DCT coefficients that vary in lighting conditions.

To order to obtain spectrum invariance for CBIR systems, texture is often represented in the random field Markov (MRF) [135]. In order to model and understand the method, Ranganathan et al [136] used probability distributions of the descriptor space of training data for lighting shifts in the feature descriptor. The degree of strength is compounded by a broad and steady weight to obtain anisotropic diffusion and to maintain gradient magnitude knowledge (i.e., 2D picture patches are implanted in 3D surfaces), which creates a strength invariance to a model [137]. The positive picture effects of uniform illumination improvements were seen in order-based approaches [11-12, 60, 138]. [138] In order to penalize the disparity between maps, instructions for such pixels are used. Only locally stable pixel couples are picked and order is outlined for each pair chosen to determine the necessary penalty. The relative strength histogram (HRI) is used for encoding the pixel order of Raj et al. [11] with regard to the entire region. They also suggested CSLTP, a generalization of the CSLBP, which was combined with HRI in order to integrate complementary knowledge. Intrinsically invariable in monotonous shifts in intensity [12], the local pressure order template (LIOP) is added. LIOP is created up of instructions between the intensity values of each pixel of the image's adjacent sample points. Tang et al. [60] implemented an ordinary spatial distribution local OSID role descriptor. The pixel strength values are divided into both spatial and ordinal areas by the OSID descriptor. Although these apps function well, they do not cope with nuanced or consistent lighting variations when the photos shift in intensity uniformly.

2.5Boosting Performance of Image Descriptors

Various descriptive interfaces are recommended, utilized and commonly accessible for image retrieval [20-21, 83, 113]. The color, texture and local picture details have been used by these approaches to construct the function descriptor. The LBP and its derivatives are determined primarily using the raw strength [1, 16, 18, 20, 142-147] values. Some researchers did some preprocessing prior to feature extraction in order to use the richer local knowledge. Such instances are Local Binary Edge Pattern [21], Sobel Local Binary Pattern (SOBEL-LBP) [139)), Semi Structure Local Binary Pattern [140], and SS-3D-LTP [83]. In order to boost efficiency the descriptors used just a few filters. The preprocessed photos specifically linked by James to facial recognition through multiple filters [141] although he has not used descriptor control over multiple filtered pictures.Recent problems require near-infrared (NIR) face scanning [142, 148] as well. Images of the same face are negatively correlated under different lighting conditions, whereas images of the same subject are closely correlated with close-infrared images [148]. Furthermore, near-infrared photographs are best equipped for indoor and mutual users [148]. Hollingsworth et al. are studying the output both of person and machinery under near-infrared light and visible light utilizing periodical biometrics [149]. The writers used an NIR face picture as the probe during the annotation of the visual face photos in a recent study of visible and near-infrarouge face-images.[150] One of the most basic matrix computations in linear numerical algebra[151] is the Singular Value Decomposition (SVD). The generalized variant of linear filtering theory or a method for image enhancement will simply be named [152, 153]. SVD employs many specific styles, including signal analysis ([154]), gate classification (155), picture encoding (156), picture labeling (157), image stag analysis [158], picture compression ([159]) and face identification (160), etc. Singh et al. [161] implemented a novel concept to decompose and view optical color images with multi-resolution sub-bands. Essentially, they have applied the SVD over the picture regions and then form the four sub bands. In [162-163], the SVD over the face picture is used to recognise a solid image. The above surveyed literature indicates that SVD is used as a tool in many applications quite effectively; it is not analyzed along with other descriptors.

3. Problem Formulation

In the research paper we noticed the following study holes, centered on a literature review and comparative analysis of various state-of - the-art methods:

- The local order descriptor provided very positive results for the area that coincides with specific transformations. For the number of nearby neighbors considered [12] the magnitude of those term grows exponentially. Therefore, after a certain number of nearby neighbors, alignment between 2 regions becomes unlikely. One of the problems of a local descriptor focused on the recent order is to hire a number of local neighbors in the building of the descriptor thus retaining fair duration of function.

- The interaction of the core with its neighbors and the interaction between neighborhoods was shown by most local descriptors [16, 18-20, 32-33, 83]. So few descriptors have treated all forms of relationships; nevertheless, such descriptors have a rather broad aspect. We defined it as a study void through which it is important to examine descriptors that cover all types of relationships-i.e. between the neighbors and the core and their neighborhood, without raising too much the scale.

- Built to date [105-106, 108-109] by means of multi-channel picture information, color and texture descriptors are subject to the robust nature or the capacity for discrimination. Many of the current multi-channel descriptors did not encode the descriptor with the cross-channel information. One of the research challenges is also listed, in which distinctive and reliable descriptors which use cross-channel knowledge need to be investigated.

- The variations in lighting are one of the big machine vision issues. There are literature approaches, for example [115-116, 120], that are not stable. Many accessible approaches perform well with small variations in lighting, but they do not perform in the event of dramatic shifts in lighting [16, 18-19]. The illumination intensity has been described as one of the research holes that must be tackled because there are many environmental factors which render the illumination difference in the picture very obvious.

- In combination with other methods, the efficiency of the local descriptors is enhanced [21, 139-140] for different applications. It is also known as one of the work limitations in which some strategies that can be used for local descriptors are needed to increase their efficiency for various computer vision applications.

4. Future Scopes

We have observed the following future directions on the basis of the performance of the proposed descriptors:

- The region based descriptors mostly designed for the grayscale images; it can be explored for the color images too.

- The performance of local descriptors can be further improved by utilizing the local neighborhood information more effectively.

- The color descriptors are still having the dimensionality problem which can be tackled further by designing the more efficient color descriptors.

- The sensitivity to the illumination problem of color descriptors can be explored to introduce more illumination robust descriptors.

- The performance of descriptors proposed for the one type of database can be explored with the other kind of databases.

- Deep learning is being used very actively nowadays to develop the features at the intermediate layers.

This may also one of the future works to integrate the existing descriptors with the deep learning based approaches.

5. Conclusion

We analyzed the image function descriptors dependent in this paper on their properties, such as or without the area, for the grayscale picture or the color picture, for the natural picture or biomedical picture or textural picture or facial picture, for some robustness against specific geometric and photometrical transformations, for some pre-oral transformation. Latest state-of - the art descriptors have carried out literature surveys and study comparisons.

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