A Survey paper on the Extraction of Identical Similarity feature points in Image

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Abstract —Feature extraction algorithms such as Scale Invariance Featured Transformation (SIFT), Speed Up Robust Features (SURF),Principal Component Analysis - Scale Invariance Featured Transformation (PCA-SIFT) and Local Binary Pattern (LBP) were compared in detail in this paper. All these algorithms uses robust and rugged feature extraction algorithms. Among these algorithms SIFT is well known for its high stability and find the salient points by using Difference of Gaussians. SIFT is more stable in many situations but it is slow when compared to other methods. SURF is the fastest algorithm which exhibits very good performance as the same as SIFT. The Fast Hessian matrix used in SURF makes it triple times faster than Gaussians of Difference. The third algorithm PCA-SIFT has good performance in image rotation as well as variation in illumination of image element and it is faster than SIFT. The fourth algorithm, Local Binary Pattern (LBP) employs comparison of center pixel with the neighborhood pixels in an image. This algorithm uses simple computations which yields faster response and also very robust in feature extraction.

Index Terms—Feature extraction, Scale Invariant feature Transform,Speed Up Robust Features, Principal Component Analysis-Scale Invariance Featured Transformation andLocal Binary Pattern.

I. INTRODUCTION

Feature extraction is one of the technique which is used for dimensional reduction in images. It is mainly used in pattern recognition and also in image processing. When the image given as input to any algorithm is very big for processing due to the presence of lot of redundant information, then the input image shall be changed to a reduced form of representation by retaining only the set of features which are not redundant. Converting the input image into a set of feature vectors (non redundant features) are called feature extraction. If the extraction of features are accurately chosen, then the relevant information can be extracted as the features set from the input image to accomplish the specific task. Thus the extracted features are used as input instead of using the full size image.

Feature extraction includes reducing the amount of inputs required to explain the huge set of input data exactly. While doing the breakdown of complex information, the major problem arises is the number of variables included. Investigation with more number of variables will require more amount of memory, complex computations or algorithm of classification which outfits the available required samples and performs poorly while applying to new samples. Feature extraction is one of the common term for developing various combinations of variables to get away from this type of problems, but describes the data with high and better accuracy.

Feature extraction technique is used in the domain of image processing. In image processing, the images or videos are applied with different algorithms, to identify and to separate the various required portions or features like shape in the image. Some of the low level feature extraction methods are edge detection, Blob detection, corner detection etc. For Shape based feature extraction, thresholding and template matching can be used.
In a basic image, it is necessary to extract the robust features. Salient points are the essential points that represents the lines, blobs, corners, edges etc. These salient points are unchangeable due to change in illumination, 3D image rotation and scaling. These points are always repeatable and this determines the reliability of the salient points. In this paper, the various feature extraction techniquessuch as Scale Invariance Featured Transformation (SIFT) [1], Speed Up Robust Features (SURF) [2], Principal Component Analysis-Scale Invariance Featured Transformation (PCA-SIFT) [3] and Local Binary Pattern (LBP) [4] are discussed in detail.

II. ORGANISATION OF THE PAPER

The remaining portion of the survey paper is organized as mentioned. SectionIII describes the different types of feature extraction techniques. The Comparison ofvarious feature extraction techniques and the discussions are given in Section IV. Conclusions are specified in Section V.

III. FEATURE EXTRACTION TECHNIQUES

The different types of feature extraction techniques discussed here are

1. Scale Invariance Featured Transformation
2. Speed Up Robust Features
3. Principal Component Analysis-Scale Invariance Featured Transformation
4. Local Binary Pattern

Type 1: SCALE INVARIANCE FEATURED TRANSFORMATION [SIFT]

This is the most commonly used similarity feature identification procedure, which is utilized to identify, extract and define the common points in picture images. The flow of SIFT algorithm is as follows

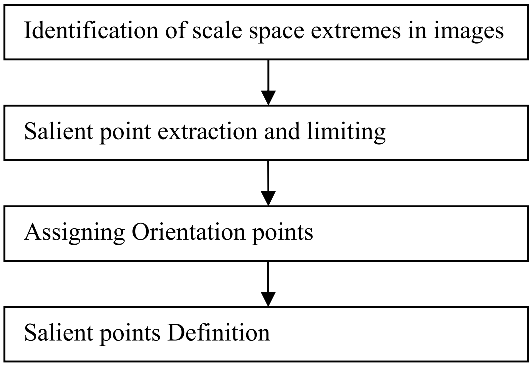


Fig 1: Flow of SIFT algorithm

Flow (a) Identification of Scale space extremes in Images:

In this step key points are extracted. These points are called salient points. For the Identification of salient points we perform useful and common Gaussians limiting at different scale points [5] of the picture images and then the difference of successive Gaussians limiting points are taken. Salient points are noted by taking the highest and lowest of the subtraction of the Gaussians [6] at different scale points.[20]

In detail, subtraction of Gaussians (SoG) can be defined as S(p,q,ρ)

$$S(p,q,\rho) = M(p,q,l_i\rho) - M(p,q,l_j\rho) \text{ ---------} \quad (1)$$

In (1), $M(p,q,l\rho) = G(p,q,l\rho) * m(p,q)$

where
m(p,q) is the normal Image under consideration
G(p,q,lρ) is the Gaussians limit points at scale point lρ
M(p,q,lρ) is the convolution of the normalimage under consideration with the Gaussians limit points at scale point lρ.

Subtraction of Gaussians (SoG) [7] at $l_i\rho$ and $l_j\rho$ points is simply means the SoG points between $l_i\rho$ and $l_j\rho$. For Scale space extremes Identification original image is simply multiplied with the time shifted version of Gaussians limiting and then collected by ρ, 2ρ, 4ρ, 8ρ, ……. till $l_i$and then the Subtraction of Gaussians images are taken.[19]

Once Subtraction of Gaussians is calculated, salient points are framed by considering the highest or the lowest of the SoG images at various points. The above said points are identified based on the similarity between pixel and eight neighboring points at same scale. The lowest or highest values of all compared pixels are framed as the encouraging salient points. The salient points can also be obtained by taking the Laplace Transform of the Gaussians function. In this method, the key points are the common maxima and minima points [8] with respect to spatial image points.

Flow (b) Salient point extraction and limiting:

Once Scale Space Extremes [9] are identified, SIFT eliminates the low valued salient points and further limits the salient points, which are the part of the edges in the picture images. In flow (a), we obtained lot of salient points but all the above points do not have high pixel values which defines the stability of the pixel. For finding out high candidature salient point's interposition of adjacent values are taken to exactly identify its location. This flow interprets the interposition position of the extremes which gives stable and accurate points. The SoG, S(p) is expanded using a well-known mathematical tool, Taylor's series expansion to find out the interposition with the candidature salient points as the start points. Mathematically, Taylor's series can be expanded as given below.

$$S(p) = S + \frac{dS^t}{dp} p + 0.5\, p^t \frac{d^2 S}{dp^2} p$$

where

S and its partial derivatives are extracted based on the candidature salient points.

p = (p,q,ρ) is the difference from this point.

The extreme valuep$^\wedge$, is given by the first derivative of p$^\wedge$ with p and p turns to zero. If the difference p$^\wedge$ is more than 0.5 it means that this extreme is closer to other salient point. In this procedure, the candidature salient point often changed and interposition at the point is taken. The next step is to eliminate the salient points with low values. To perform this operation, the Taylor's series S(p) second order is calculated at the differencep$^\wedge$, then the contrast values are calculated. If the contrast value is below 0.3, the candidature salient point is eliminated. If it is greater than 0.03, the candidature salient point is kept in the image space q+p$^\wedge$, where q is the origin of the corresponding salient point.

The SoG has good points at the image edges even though candidature salient points suffers too little noise. But as far as stability is concerned, such salient points are to be discarded as they have good edge values.

If some peaks are weak and poor in the SoGs, the principal curvature at image edge is greater than the principle curvature across it. The next step is to find out the principal curvature at the edge images, this can be found out by calculating the eigen values of Hessian matrix.

$$He = \begin{bmatrix} S_{pp} & S_{pq} \\ S_{pq} & S_{qq} \end{bmatrix}$$

In this Hessian matrix, the eigen values are directly related to principal curvatures of S. The principal curvatures are given by the eigen values γ/α, where γ denotes the high value and α denotes the low value. Ratio of the above serves our purpose. Sum (S) of Sppand S_{qq}denotes the addition of eigen values and the determinant $S_{pp}S_{qq} - S_{pq}^2$, gives the multiplication. The change in the two eigen values reflects the difference in principal curvature of S.

Flow (c) Assigning Orientation points:

In this flow, salient points [10] are given some orientations equivalent to the original image gradient points. The above flow is an important step in getting invariance to clockwise turning because salient point descriptor will be better understood based on this orientation and invariance can be achieved through clockwise turning of the image. All mathematical calculations are carried out on the Gaussians limited image M(p,q,ρ) at the salient points [13] scale ρ. The local image considered M(p,q) at scale ρ amplitude gradient is given by a(p,q) and orientation angle is given by φ(p,q). These are calculated using the pixel values.

$$a(p,q) = \sqrt{\begin{matrix}[M(p+1,q) - M(p-1,q)]^2 + \\ [M(p,q+1) - M(p,q-1)]^2\end{matrix}}$$

$$\phi(p,q) = a\tan 2[M(p,q+1) - M(p,q-1), @ \;\; M(p+1,q) - M(p-1,q)]$$

In the similar way the amplitude gradient and the angle calculations for different gradients are made for each pixel in the surrounding region around the salient points in the original image M. Angle orientation histograms are formed with 36 points and each points have 10 degrees each. The Individual samples in the nearby points depends upon its individual amplitude gradients. The dominant angle orientations will have peaks in the above said histograms, then the angle orientations in these histogram with highest peak are given to the salient points. In some cases, more than one orientation will be assigned, in this case more salient points should be created but these salient points are placed in the same image pixels and the scale as per the local salient points [16] for all extra angle orientations.

Flow (d) Salient point descriptors:

In the above said flows, one can find the positions of salient points [11] at some scales and angle orientations are mapped to those points. Here invariance clockwise turning and scaling are ensured. In this salient point descriptor we are calculating a descriptor vector for every salient points so that the above descriptor is invariant with respect to variations involving three dimensional mapping, illumination etc. This flow is carried out on a particular image which is very similar to the scale of the salient points [12].

Primarily different orientation graphical representations are generated on 4*4 image nearby points each containing eight intensity values. The above graphical representations are created from amplitude and angle orientation of intensity values surrounding 16*16 points across the salient point. This is generated such a way every graphical representation contains pixel values from 4*4 intensity values of actual surrounding region. The amplitudes were again multiplied with Gaussian variable where ρ corresponds to 0.5 times the descriptor window width. Further to this the descriptor will be the vector corresponding to intensity values of above graphical representation. From the above we have 16 graphical representations with the eight points such that the vector is having 128 pixel values. The above vector is divided by the total length to support invariance that is caused by the difference in the illumination of images.

In the above flow the length of the descriptor is 128 which is on the higher side. The descriptor less than 128 performs poorly. High value descriptors [17] performs well but there is a disadvantage of more sensitivity against noise. It is proved that the accuracy is more than 50% for 50º changes. Hence SIFT descriptors where robust against small changes.

Type2: SPEEDED UP ROBUST FEATURES [SURF]

The flow of the SURF algorithm consists of the following steps.

Formation of Summed up image

↓

Getting the point of interest in images
(Fast Hessian matrix identification)

↓

Allotting angle orientations to descriptors.

↓

Formation of descriptors

Fig 2: Flow of SURF algorithm

The other commonly used Feature extraction technology is Speeded Up Robust Features (SURF). SURF algorithm [7] creates number of features among the input image and the image available in the database for comparison.

Flow (a) Formation of Summed up image:

The Summed up Image (Integral image) is generated in various step of SURF mainly to increase the speed. The above said image is given in equation (a)

$$S\sum(p,q) = \sum_{m=0}^{p}\sum_{n=0}^{q} S(m,n) \qquad \text{-----------------} \ (a)$$

Flow (b) Getting the point of interest in images:

To use the summed up image one should input four intensity values for generating the integral with our own size from the query image. SURF algorithm adopts the usage of determinant of $H_e(p,q)$ to pin point the interest point [14] in images.

$$\mathbf{He(p,q)} = det\begin{pmatrix} \frac{\partial^2 f1}{\partial p^2} & \frac{\partial^2 f1}{\partial p \partial q} \\ \frac{\partial^2 f1}{\partial p \partial q} & \frac{\partial^2 f1}{\partial q^2} \end{pmatrix}$$

$$\mathbf{He}(\overline{p}) = Dpp(\overline{p})\, Dqq(\overline{p}) - \left(\mathbf{0.9}Dpq(\overline{p})\right)^2$$

$$\bar{p} = (p,q,r) \qquad \text{-------------------------} \ (b)$$

Equation (b) explains the Hessian matrix usage for 2D final images.

Flow (c) Allotting angle orientations to descriptors:

Detection in fast Hessian mode regenerates equation (b) in the following ways.

1. Partial differentiation is replaced by individual image convolution with the corresponding kernels of Gaussians.
2. Kernels of Gaussian are placed in the image positions by corresponding size.

$$He(p) = He + \frac{\partial He^T}{\partial p} p + \frac{1}{2} p^T \frac{\partial^2 He}{\partial p^2} p$$

$$\bar{p} = \frac{\partial^2 He^{-1}}{\partial p^2}\frac{\partial He}{\partial p}$$

Flow (d) Formation of descriptors:

Weighting is given by the parameter r which is also called as scale space. Based on the above assumption the weight of the individual point is given by

$$Wx = \frac{No.of\ identified\ images\ at\ x}{No.of\ object\ images}$$

Type3: PRINCIPAL COMPONENTS ANALYSIS - SCALE INVARIANCE FEATURED TRANSFORMATION [PCA- SIFT]

PCA- SIFT[15] has very good properties in rotation and illumination changes in images. It is a robust technique usually used to pin point the salient point patches. It also helps to convert large dimensional intensity values with small dimensional image spaces. In this technique PCA-SIFT employs principal curvature analysis method in place of normal graphical representation (histograms) which is used for normalization purposes. As compared with the SIFT technique [18], the image feature vector is very small and the same is effectively utilize for the similar matching protocols. Euclidean distance method is effectively utilized to check the difference vectors belong to one salient points in various input images. PCA- SIFT produces high speed matching as they require very less components and minimum storage area. As the dimensionality value D = 20 this gives very good benefits in spatial images.

PCA- SIFT generally takes the input images similar to a SIFT technique. The main flow includes the intensity value point scale and rotation of the salient point. Here, we consider an n*n size surrounded over the salient point which is rotated to a particular direction. This technique is well explained by the flow given below.

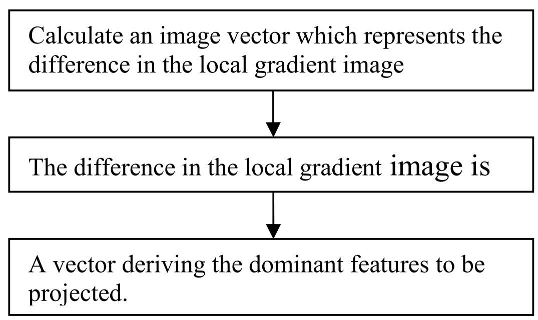


Fig 3: Flow of PCA-SIFT algorithm

The above vector is much smaller in size in compared with the SIFT[21] vector. Hence PCA-SIFT technique employs very small matching algorithms with improved speed. In this technique, feature vectors belonging to same salient point is extracted by taking the Euclidean distance between them.PCA-SIFT is very commonly used technique for object recognition, Feature extraction and face recognition. The main disadvantage in PCA- SIFT [22] is the basic assumption the algorithm does with the distribution of Gaussians. This algorithm has a primary disadvantage in the linear combination of orthogonal functions but this algorithm is extensively used because of its simplicity.

Flow (a) Calculation of image patch in offline mode:

PCA- SIFTexplicitly offers a simple conversion from high dimensional images to small dimensional image intensity points. In this algorithm, the image patches can be computed much before and it is stored in the memory. The space input vector can be formed by mixing lateral and longitudinal gradient points for the n*n patch surrounding by the salient point. Thus the input vector is a long array. Normalization is performed on this vector to take care the illumination variations in the image pixel. The patches described above will have certain important characteristics as listed below.

1) It is the intersection of the maximum points in a image space
2) If 3D rotated the dominant characteristics will be confined to the vertical axis
3) Most of the dominant characteristics for the scale space to the salient point will be created.

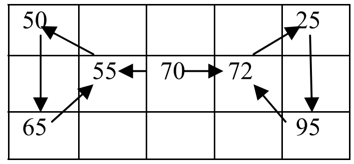
Flow (b) Representation of features:

Feature vectors corresponding to image patches can be found out by employing large array image gradient and mapping it to the feature space. In SIFT algorithm the element vector size is of 128 elements. But using PCA-SIFT algorithm enormous space benefits can be achieved.

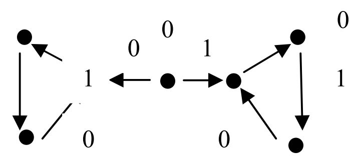
Type4: LOCAL BINARY PATTERN [LBP]

The image textures can be efficiently characterized by using yet another powerful operator called Local Binary Pattern (LBP) [23]. The output of this operator is binary which is obtained by taking a center pixel value and comparing it with the nearby pixel values. While comparison if the center pixel value is less than the neighborhood value, then binary '1' is set else '0'. As this algorithm has very simple computations and high power in discrimination this technique is widely used in face recognition application [27]. The great strength of this algorithm is to identify the grey scale variations due to certain change in illumination. In certain real time applications, this technique is widely used because of its robustness and simple mathematical operations. As this algorithm compares 3*3 nearby pixel elements in an image some of the useful features may get missed, which is considered as major bottleneck of this operator.[30]

Another improved operator called Identical Structure of Local Graphs [24] in which more neighborhood image pixels are considered and compared in such a way that the comparison is done based on the symmetrical graph theory [26]. The output of this operator is again a binary pattern with less computational time. The graphical representation [29] is said to be symmetric because three neighborhood pixels are taken from the left side of the center pixel and three on the right side. No common information on the nearby pixels are available in this graphical operation [28]. This technique is wide spread as the comparison takes place at a distance of one and two between the nearby pixels. Because of this feature, dominant features of the images can be extracted very easily.



After Thresholding, the values are converted to binary.



The Binary equivalent of the corresponding values,

		42		

Fig 4: Identical Structure of Local Graphs

IV. DISCUSSION

The various features extraction techniques used in image retrieval are discussed in theTable 1, along with their description and disadvantages.

TABLE 1 COMPARISON OF THE ALGORITHMS

No	Method Used	Description	Disadvantage
1	SIFT	This technique uses Gaussians limitingat different scale points. This method also shows its high stability, in case of blurred noise and 3D rotation of scaled images.	Thematching success in the SIFT algorithm is determinedby howthe localization error in the representation of image features has been chosen.
2	SURF	This algorithm is highly stable and yields very high speed matching results in practical scenarios. The detector used in SURF is n times faster than the Difference of	Even though the algorithm seems to be faster in certain cases where 3D image rotation plays an important role, so the algorithm performance need improvement.

		Gaussians and Hessian Laplace detector most commonly used in other matching algorithms.	
3	PCA SIFT	This algorithm is having high speed and has advantages in storing as it uses small dimensions. This approach performs well in 3D rotation and illumination changes of images.	This approach is vulnerable to image registration error. The blurred noise and image scaling performances to be addressed and improved.
4	LBP	This algorithm has high power in the discrimination of image features. Also this algorithm uses very simple mathematical computations hence faster. This is also known for its robustness in image feature extraction.	If LBP operator compares the 3*3 neighborhood pixel alone some of the useful features may get missed.

In this paper, the parameters such as speed and the rotation of the image datasets are evaluated. On comparing the processing speed, SURF is the fastest one and SIFT is slow but it has more number of matches.

Fig 5: The Time taken for processing from group A of image set.

TABLE 2 COMPARISON OF THE TIME TAKEN FOR PROCESSING

Parameters	**SIFT**	**PCA-SIFT**	**SURF**
Total matches	271	18	186
Time taken (ms)	2.1537e+007	2.1396e+007	3362.86
10 matches taken	2.1480e+007	2.0969e+007	3304.97

The influence of rotation varies in these methods. SIFT detect most changes and are stable to rotation. SURF does not perform well in case of rotation and it finds only least matches. PCA SIFT is better than SURF but can able to find only one match among the first ten matches.

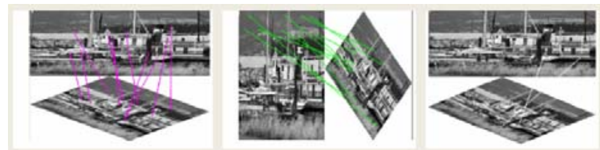


Fig 6: Rotation comparison

In figure 6, the first and the second picture represents the matches in SIFT and the PCA- SIFT and the third picture represents the matches in SURF with respect to rotation of images.

Fig 7: Graph showing the rotation comparison

V. CONCLUSION

In this survey paper, different feature extraction techniques in image processingsuch as SIFT, SURF, PCA-SIFT and LBP arestudied in a detailed way and its advantages and disadvantages are listed out. Out of the above techniques, some techniques are very robust and rugged. But they lack in speed. Some algorithms like LBP are very faster due to simple calculations but as it samples and compares less neighborhood values some of the dominant features are missed. So depending upon the application, a feature extraction algorithm can be chosen. So in conclusion, effective utilization of image Hessian matrices and fast computing devices may be employed.

REFERENCES

[1] D. G. Lowe,“Distinctive image features from scale-invariant keypoints,” Int. J. Comput. Vis., vol. 60, no. 2, pp. 91–110, Nov. 2004.
[2] H. Bay, T. Tuytelaars, and L. Van Gool, “SURF: Speeded up robust features,”in Proc. 9th ECCV, 2006, pp. 404–417.
[3] Y. Ke and R. Sukthankar, “PCA-SIFT: A more distinctive representation for local image descriptors,” in Proc. IEEE Comput. Soc. Conf. CVPR, Jun./Jul. 2004, pp. II-506–II-513.
[4] MohdFikriAzli Abdullah, MdShohelSayeed, KalaiarasiSonaiMuthu, HousamKhalifaBashier,

AfizanAzman,SitiZainab Ibrahim, “Face recognition with Symmetric Local Graph Structure (SLGS)”Expert Systems with Applications 41 (2014) 6131–6137.

[5] Nagar, A., Saxena, A., Bucak, S., Fernandes, F., &Bhat, K. P. (2013, November). Low complexity image matching using color based SIFT. In Visual Communications and Image Processing (VCIP), 2013 (pp. 1-6). IEEE.

[6] HunnyMehrotra, Phalguni Gupta, and JamunaKanta Singh, DakshinaRanjanKisku, “SIFT-based Ear Recognition by Fusion of Detected Keypoints from Color Similarity Slice Regions”, 2009.

[7] P. fan; A. men; M. Chen (2013),“Color –SIRF: A SURF Descriptor with Local Kernel Color Histogram”,IEEE,2009,pp.726-730.

[8] Schmid, C., andMohr, R. 1997. Local grayvalue invariants for image retrieval. IEEE Trans. on Pattern
Analysis and Machine Intelligence, 19(5):530-534.

[9] Fergus, R., Perona, P., and Zisserman, A. 2003. Object class recognition by unsupervised scaleinvariant
learning. In IEEE Conference on Computer Vision and Pattern Recognition, Madison,Wisconsin, pp. 264-271.

[10] Funt, B.V. and Finlayson, G.D. 1995. Color constant color indexing. IEEE Trans. on Pattern Analysisand Machine Intelligence, 17(5):522-529.

[11] Lowe, D.G. 1991. Fitting parameterized three-dimensional models to images. IEEE Trans. on Pattern
Analysis and Machine Intelligence, 13(5):441-450.

[12] Lowe, D.G. 2001. Local feature view clustering for 3D object recognition. IEEE Conference onComputer Vision and Pattern Recognition, Kauai, Hawaii, pp. 682-688.

[13] Schmid, C., andMohr, R. 1997. Local grayvalue invariants for image retrieval. IEEE Trans. on Pattern Analysis and Machine Intelligence, 19(5):530-534.

[14] Mikolajczyk, K., Schmid, C.: An affine invariant interest point detector. In: ECCV.(2002) 128 – 142

[15] Ke, Y., Sukthankar, R.: PCA-SIFT: A more distinctive representation for localimage descriptors. In: CVPR (2). (2004) 506 – 513

[16] Matas, J., Chum, O., M., U., Pajdla, T.: Robust wide baseline stereo from maximallystable extremal regions. In: BMVC. (2002) 384 – 393

[17] Mikolajczyk, K., Schmid, C.: A performance evaluation of local descriptors. PAMI27 (2005) 1615–1630

[18] Mikolajczyk, K., Tuytelaars, T., Schmid, C., Zisserman, A., Matas, J., Schaffalitzky,F., Kadir, T., Van Gool, L.: A comparison of affine region detectors. IJCV
65 (2005) 43–72

[19] Mikolajczyk, K., Schmid, C.: Indexing based on scale invariant interest points. In:ICCV. Volume 1. (2001) 525 – 531

[20] Lowe, D.: Object recognition from local scale-invariant features. In: ICCV. (1999)

[21] Kadir, T., Brady, M.: Scale, saliency and image description. IJCV 45(2) (2001)83 – 105

[22] Brown, M., Lowe, D.: Invariant features from interest point groups. In: BMVC.(2002)

[23] Bai, G., Zhu, Y., & Ding, Z. (2008). A hierarchical face recognition method based on local binary pattern. In 2008 congress on image and signal processing (pp. 610–614). IEEE. http://dx.doi.org/10.1109/CISP.2008.520.

[24] Bartlett, M. S., Movellan, J. R., &Sejnowski, T. J. (2002). Face recognition by independent component analysis. In IEEE transactions on neural networks (13, pp. 1450–1464).

[25] Jin, H., Liu, Q., Lu, H., & Tong, X. (2004). Face detection using improved LBP under bayesian framework. In Third international conference on image and graphics
(ICIG’04) (pp. 306–309). IEEE.

[26] Yang, H., & Wang, Y. (2007). A LBP-based face recognition method with hamming distance constraint. In Fourth international conference on image and graphics (ICIG 2007) (pp. 645–649). IEEE.

[27] Zhao, G., &Pietikainen, M. (2007). Dynamic texture recognition using local binary patterns with an application to facial expressions. IEEE Transactions on Pattern Analysis and Machine Intelligence, 29(6), 915–928.

[28] Wiskott, L., Fellous, J., Krugerl, N., Malsburg, C., & Von Der (1997). Face recognition by elastic bunch graph matching. IEEE transactions on pattern analysis and machine intelligence, 19(7), 775–779.

[29] Bashier, H. K., Abusham, E. E. A., & Khalid, F. (2012). Face detection based on graph structure and neural networks. Trends in Applied Sciences Research, 7(8), 683–691.

[30] Sayeed, S., Yusof, I., Bashier, H. K., &Hossen, J. (2013). Plant identification based on leaf shape and texture pattern using local graph structure (LGS). Australian Journal of Basic and Applied Sciences, 7(11), 29–35.