iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 6 **Issue:** III **Month of publication:** March 2018

DOI: http://doi.org/10.22214/ijraset.2018.3035

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 6.887
Volume 6 Issue III, March 2018- Available at www.ijraset.com

Survey on Feature Extraction Techniques in Image Processing

Soumya Balan P[1], Prof. Leya Elizabeth Sunny[2]
[1, 2] *Department of Computer Science and Engineering, Mar Athanasius College of Engineering, Kothamangalam, Kerala, India*

Abstract*: In machine learning, pattern recognition and in image processing, feature extraction starts from an initial set of measured data and builds derived values (features) intended to be informative and non-redundant, facilitating the subsequent learning and generalization steps, and in some cases leading to better human interpretations. Feature extraction is related to dimensionality reduction. When the input data to an algorithm is too large to be processed and it is suspected to be redundant then it can be transformed into a reduced set of features (also named a feature vector). Determining a subset of the initial features is called feature selection. The selected features are expected to contain the relevant information from the input data, so that the desired task can be performed by using this reduced representation instead of the complete initial data. Feature extraction involves reducing the amount of resources required to describe a large set of data. When performing analysis of complex data one of the major problems stems from the number of variables involved. Analysis with a large number of variables generally requires a large amount of memory and computation power, also it may cause a classification algorithm to over-fit to training samples and generalize poorly to new samples. Feature extraction is a general term for methods of constructing combinations of the variables to get around these problems while still describing the data with sufficient accuracy.
***Keywords*: Feature Extraction, Colour, Texture, Shape, Local Binary Pattern**

I. INTRODUCTION

Image processing is a method to perform some operations on an image, in order to get an enhanced image or to extract some useful information from it. It is a type of signal processing in which input is an image and output may be image or characteristics/features associated with that image. Nowadays, image processing is among rapidly growing technologies. It forms core research area within engineering and computer science disciplines too.

Image processing basically includes the following three steps:

Importing the image via image acquisition tools;

Analysing and manipulating the image;

Output in which result can be altered image or report that is based on image analysis.

Image processing is the application of signal processing techniques to the domain of images — two-dimensional signals such as photographs or video. Image processing does typically involve filtering or enhancing an image using various types of functions in addition to other techniques to extract information from the images.

There is no universal or exact definition of what constitutes a feature, and the exact definition often depends on the problem or the type of application. Given that, a feature is defined as an "interesting" part of an image, and features are used as a starting point for many computer vision algorithms. Since features are used as the starting point and main primitives for subsequent algorithms, the overall algorithm will often only be as good as its feature detector. Consequently, the desirable property for a feature detector is repeatability: whether or not the same feature will be detected in two or more different images of the same scene.

Feature detection is a low-level image processing operation. That is, it is usually performed as the first operation on an image, and examines every pixel to see if there is a feature present at that pixel. If this is part of a larger algorithm, then the algorithm will typically only examine the image in the region of the features. As a built-in pre-requisite to feature detection, the input image is usually smoothed by a Gaussian kernel in a scale-space representation and one or several feature images are computed, often expressed in terms of local image derivatives operations.

Occasionally, when feature detection is computationally expensive and there are time constraints, a higher level algorithm may be used to guide the feature detection stage, so that only certain parts of the image are searched for features. Many computer vision algorithms use feature detection as the initial step, so as a result, a very large number of feature detectors have been developed. These vary widely in the kinds of feature detected, the computational complexity and the repeatability.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 6.887
Volume 6 Issue III, March 2018- Available at www.ijraset.com

In computer vision and image processing feature detection includes methods for computing abstractions of image information and making local decisions at every image point whether there is an image feature of a given type at that point or not. The resulting features will be subsets of the image domain, often in the form of isolated points, continuous curves or connected regions.

We are decomposing the problem of feature extraction in two steps: feature construction, briefly reviewed in the previous section, and feature selection, to which we are now directing our attention. Although feature selection is primarily performed to select relevant and informative features, it can have other motivations, including: 1. general data reduction, to limit storage requirements and increase algorithm speed; 2. feature set reduction, to save resources in the next round of data collection or during utilization; 3. performance improvement, to gain in predictive accuracy; 4. data understanding, to gain knowledge about the process that generated the data or simply visualize the data

The organization of this document is as follows. In Section 2 (Background), will give detail of the basic details of features. In Section 3 (Overview of Feature Extraction Methods in Image Processing), present your research findings analysis of those findings. In Section 4 (Analysis of Feature Extraction Methods in Image Processing) will explain the analysis of these findings. Section 5 (Conclusion) is the conclusion of these findings.

II. BACKGROUND

This section describes the Types of Image Features, colour features, texture features model and the shape features.

A. Types of Image Features

1) *Edges :* Edges are points where there is a boundary (or an edge) between two image regions. In general, an edge can be of almost arbitrary shape, and may include junctions. In practice, edges are usually defined as sets of points in the image which have a strong gradient magnitude. Furthermore, some common algorithms will then chain high gradient points together to form a more complete description of an edge. These algorithms usually place some constraints on the properties of an edge, such as shape, smoothness, and gradient value. Locally, edges have a one-dimensional structure.
2) *Corners / interest points:* The terms corners and interest points are used somewhat interchangeably and refer to point-like features in an image, which have a local two dimensional structure. The name "Corner" arose since early algorithms first performed edge detection, and then analysed the edges to find rapid changes in direction (corners). These algorithms were then developed so that explicit edge detection was no longer required, for instance by looking for high levels of curvature in the image gradient. It was then noticed that the so-called corners were also being detected on parts of the image which were not corners in the traditional sense (for instance a small bright spot on a dark background may be detected). These points are frequently known as interest points, but the term "corner" is used by tradition.
3) *Blobs / regions of interest points:* Blobs provide a complementary description of image structures in terms of regions, as opposed to corners that are more point-like. Nevertheless, blob descriptors may often contain a preferred point (a local maximum of an operator response or a centre of gravity) which means that many blob detectors may also be regarded as interest point operators. Blob detectors can detect areas in an image which are too smooth to be detected by a corner detector.Consider shrinking an image and then performing corner detection. The detector will respond to points which are sharp intheshrunk image, but may be smooth in the original image. It is at this point that the difference between a corner detector and a blob detector becomes somewhat vague. To a large extent, this distinction can be remedied by including an appropriate notion of scale. Nevertheless, due to their response properties to different types of image structures at different scales, the LoG and DoH blob detectors are also mentioned in the article on corner detection.
4) *Ridges:* For elongated objects, the notion of ridges is a natural tool. A ridge descriptor computed from a grey-level image can be seen as a generalization of a medial axis. From a practical viewpoint, a ridge can be thought of as a one-dimensional curve that represents an axis of symmetry, and in addition has an attribute of local ridge width associated with each ridge point. Unfortunately, however, it is algorithmically harder to extract ridge features from general classes of grey-level images than edge-, corner- or blob features. Nevertheless, ridge descriptors are frequently used for road extraction in aerial images and for extracting blood vessels in medical images. Low-level features can be extracted directly from the original images, whereas high-level feature extraction depends on low level features.

The issue of choosing the features from the extracted vector should be guided by the following concerns:

The features should carry enough information about the image and should not require any domain-specific knowledge for their extraction.

They should be easy to compute in order to approach the feasibility of a large image collection and rapid retrieval. They should relate well to the human perceptual characteristics since users finally determine the suitability of the images retrieved.

B. Colour Features

A colour piece (or colour feature) is a section of a publication (such as a newspaper or magazine) that focuses mainly on impressions or descriptions of the subject matter. It mainly emphasises the descriptive aspects.

Compared with operating a traditional database on an on-site physical server and storage architecture, a cloud database offers the following distinct advantages:

1) Robustness: The color histogram is invariant to rotation of the image on the view axis, and changes in small steps when rotated otherwise or scaled.
2) Effectiveness: There is high percentage of relevance between the query image and the extracted matching images.
3) Implementation simplicity: The construction of the color histogram is a direct process, including scanning the image, assigning color values to the resolution of the histogram, and building the histogram using color components as indices.
4) Computational simplicity: The histogram computation has O(x,y) complexity for images of size $x \times y$. The complexity for a single image match is linear, O(n), where n represents the number of different colors, or resolution of the histogram. 109
5) Low storage requirements: The color histogram size is significantly smaller than the image itself, assuming color quantization.

C. Texture Features

An image texture is a set of metrics calculated in image processing designed to quantify the perceived texture of an image. Image texture gives us information about the spatial arrangement of colour or intensities in an image or selected region of an image. Image textures can be artificially created or found in natural scenes captured in an image. Image textures are one way that can be used to help in segmentation or classification of images. For more accurate segmentation the most useful features are spatial frequency and an average grey level. To analyse an image texture in computer graphics, there are two ways to approach the issue: Structured Approach and Statistical Approach.

1) Textural features are:
2) Statistical measures
3) Entrop
4) Homogeneity
5) Contrast
6) Wavelets
7) Fractals

D. Shape Features

For image content description, shape is an important visual feature and one of the primitive feature. Shape content description cannot be defined exactly because measuring the similarity between shapes is difficult.

For shape feature extraction, edge matching is very important. Edge matching:

Uses edge detection techniques, such as the Canny edge detection, to find edges.

Changes in lighting and colour usually don't have much effect on image edges

1) Strategy

a) Detect edges in template and image
b) Compare edges images to find the template
c) Must consider range of possible template positions

2) *Measurements*

1) Good – count the number of overlapping edges. Not robust to changes in shape
2) Better – count the number of template edge pixels with some distance of an edge in the search image
3) Best – determine probability distribution of distance to nearest edge in search image (if template at correct position). Estimate likelihood of each template position generating image

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 6.887
Volume 6 Issue III, March 2018- Available at www.ijraset.com

III.OVERVIEW OF FEATURE EXTRACTION METHODS IN IMAGE PROCESSING

A performance evaluating of colour descriptors such as colour SIFT, Opponent SIFT, etc. are made for object and scene Recognition in [1]. These descriptors first find the regions in the image using region detectors, then compute the descriptor over each region and finally the descriptor is formed by using bag-of-words (BoW) model. Researchers are also working to upgrade the BoW model [2]. Another interesting descriptor is GIST which is basically a holistic representation of features and has gained wider publicity due its high discriminative ability [3]– [4].

In order to encode the region based descriptors into a single descriptor, a vector locally aggregated descriptors (VLAD) has been proposed in the literature [5]. Recently, it is used with deep networks for image retrieval [6]. Fisher kernels are also used with deep learning for the classification [46], [47]. Very recently, a hybrid classification approach is designed by combining the fisher vectors with the neural networks [49]. Some other recent developments are deep convolutional neural networks for imagenet classification [7], super vector coding [8], discriminative sparse neighbour coding [9], fast coding with neighbour-to-neighbour search [10], projected transfer sparse coding [11] and implicitly transferred codebooks based visual representation [12].

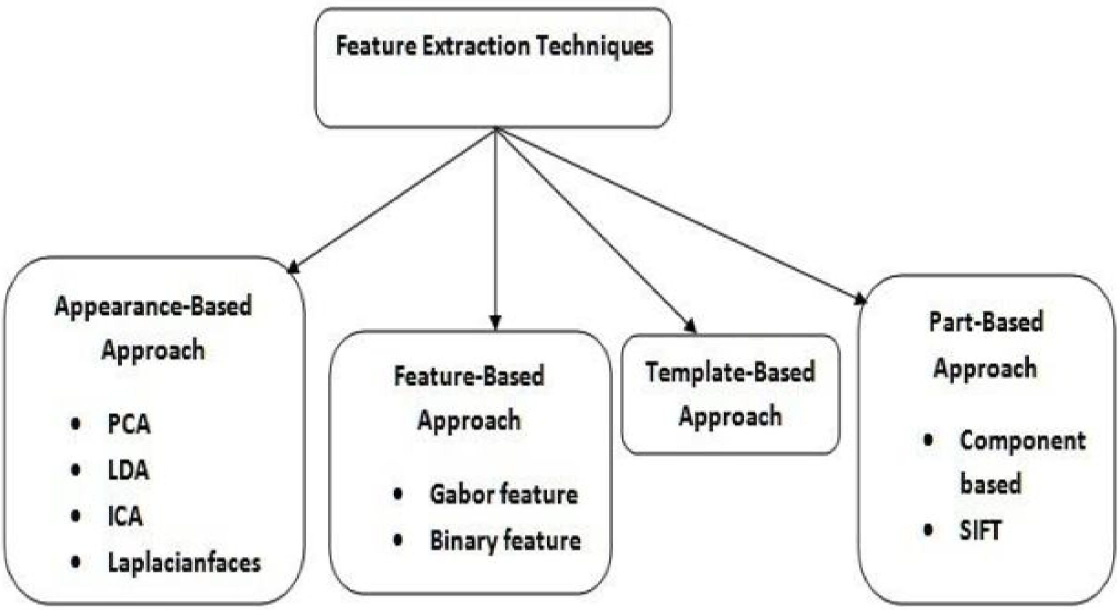


Fig. 1 Classification of Various Feature Extraction Techniques

To describe the colour images using local patterns, several researchers adopted the multichannel feature extraction approaches. LCOD basically quantized the Red, Green and Blue channels of the image and formed a single image by pooling the quantized images and finally computed the occurrences of each quantized colour locally to form the feature descriptor [13]. Similarly, RSHD computed the occurrences of textural patterns [14] and CDH used the colour quantization in its construction process [15].

Chu et al. [16] have quantized the H, S and V channels of the HSV colour image into 2, 4 and 32 values respectively and represented by 1, 2 and 5 binary bits respectively. They concatenated the 1, 2 and 5 binary bits of quantized H, S and V channels and converted back into the decimal to find the single channel image and finally the features are computed over this image. The major drawback of this category is the loss of information in the process of quantization.

A local colour vector binary pattern is defined by Lee et al. for face recognition [17]. They computed the histogram of colour norm pattern (i.e. LBP of colour norm values) using Y, I and Q channels as well as the histogram of colour angular pattern (i.e. LBP of colour angle values) using Y and I channels and finally concatenated these histograms to form the descriptor. The main problem with these approaches is that the discriminative ability is not much improved because these methods have not utilized the inter channel information of the images very efficiently.

In order to overcome the drawback of the third category, the fourth category comes into the picture where some of bits of the binary patterns of two channels are transformed and then the rest of the histogram computation and concatenation takes place over the transformed binary patterns. The mCENTRIST [18] is an example of this category where Xiao et al. [26] have used at most two channels at a time for the transformation. In this method, the problem arises when more than two channels are required to model,

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 6.887
Volume 6 Issue III, March 2018- Available at www.ijraset.com

then the author suggested to apply the same mechanism over each combination of two channels which in turn increases the computational cost of the descriptor.

Heng et al. [19] computed the multiple types of LBP patterns over multiple channels of the image such as Cr, Cb, Gray, Low pass and High pass channels and concatenated the histograms of all LBPs to form the single feature descriptor. To reduce the dimension of the feature descriptor, they selected some features from the histograms of LBPs using shrink boost method. Choi et al. [20] computed the LBP histograms over each channel of a YIQ colour image and finally concatenated to from the final features.

Zhu et al. [21] have extracted the multiscale LBPs by varying the number of local neighbours and radius of local neighbourhood over each channel of the image and concatenated all LBPs to construct the single descriptor. They also concatenated multiple LBPs extracted from each channel of RGB colour image [22]. The histograms of multiscale LBPs are also aggregated in [23] but over each channel of multiple colour spaces such as RGB, HSV, YCbCr, etc. To reduce the dimension of the descriptor, Principle Component Analysis is employed in [17].

IV. ANALYSIS OF FEATURE EXTRACTION METHODS IN IMAGE PROCESSING

The survey is conducted for finding methods of content based image retrieval process. In addition of that the features vector estimation and various frequently used techniques are also evaluated. In near future this technique is utilized to introduce a new image feature calculation technique, which is used for color image recognition and clearer and efficient edge detection.

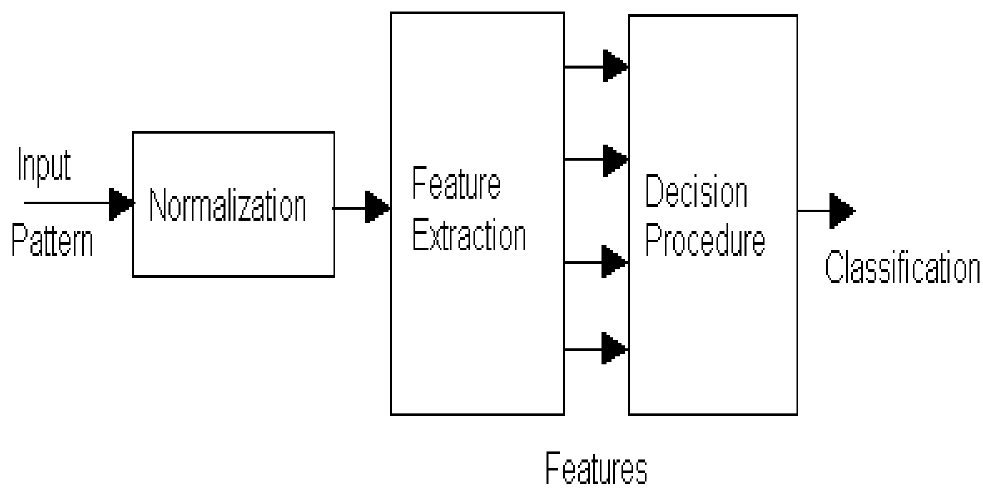


Fig. 2 The feature extraction process

There are lots of drawbacks in the existing methods discussed in the previous section. There will be loss of information in the process of quantization and may be the dimension of the final descriptor is very high.

Most of them are not suited for real time computer vision applications. Other common drawbacks consist of:

A. Discriminative ability is not much improved because these methods have not utilized the inter channel information of the images very efficiently
B. Problem arises when more than two channels are required to model which increases the computational cost of the descriptor

V. CONCLUSION

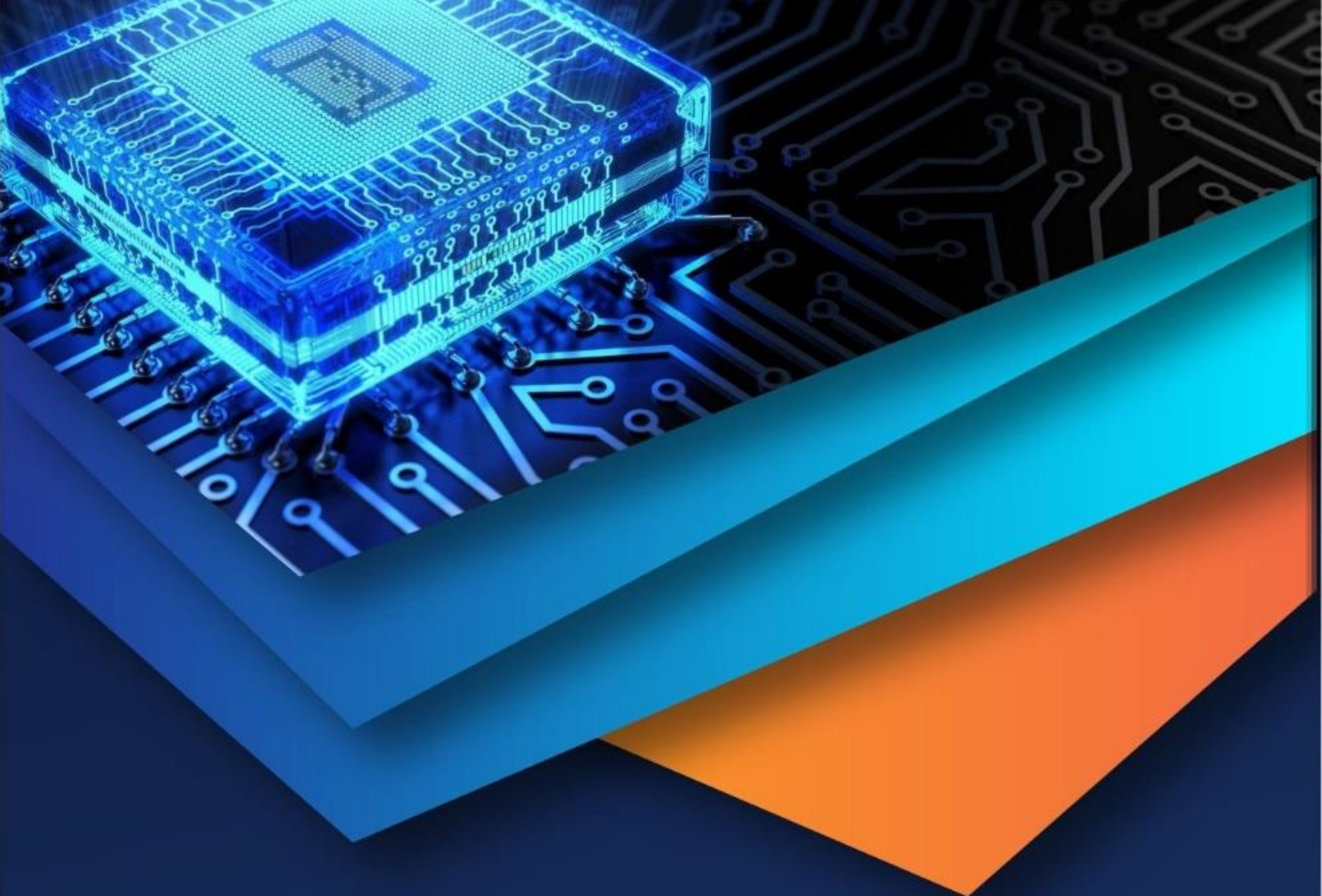
Before discussing the extraction of feature points it is necessary to have a measure to compare parts of images. The extraction and matching of features is based on these measures. Besides the simple point feature a more advanced type of feature is also presented. Feature extraction technique is used to extract the features by keeping as much information as possible from large set of data of image. Local features refer to a pattern or distinct structure found in an image, such as a point, edge, or small image patch. They are usually associated with an image patch that differs from its immediate surroundings by texture, color, or intensity. Feature extraction projects a data set with higher dimensionality onto a smaller number of dimensions. As such it is useful for data visualization, since a complex data set can be effectively visualized when it is reduced to two or three dimensions. Some applications of feature extraction are latent semantic analysis, data compression, data decomposition and projection, and pattern recognition. Feature extraction can also be used to enhance the speed and effectiveness of supervised learning.

VI. ACKNOWLEDGMENT

I owe my sense of gratitude and sincere thanks to Prof. Leya Elizabeth Sunny for her guidance, constant supervision, encouragement and support throughout the period of this thesis work.

REFERENCES

[1] S K. E. A. van de Sande, T. Gevers, and C. G. M. Snoek, “Evaluating color descriptors for object and scene recognition,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 32, no. 9, pp. 1582–1596, Sep. 2010.
[2] H. Jégou, M. Douze, and C. Schmid, “Improving bag-of-features for large scale image search,” Int. J. Comput. Vis., vol. 87, no. 3, pp. 316–336, May 2010.
[3] Oliva and A. Torralba, “Modeling the shape of the scene: A holistic representation of the spatial envelope,” Int. J. Comput. Vis., vol. 42, no. 3, pp. 145–175, 2001.
[4] M. Douze, H. Jégou, H. Sandhawalia, L. Amsaleg, and C. Schmid, “Evaluation of gist descriptors for Web-scale image search,” in Proc. ACM Int. Conf. Image Video Retr., Jul. 2009, pp. 19–27.
[5] H. Jégou, M. Douze, C. Schmid, and P. Pérez, “Aggregating local descriptors into a compact image representation,” in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., Jun. 2010, pp. 3304–3311.
[6] J. Y.-H. Ng, F. Yang, and L. S. Davis, “Exploiting local features from deep networks for image retrieval,” in Proc. IEEE Int. Conf. Comput. Vis. Pattern Recognit., DeepVis. Workshop (CVPRW), Apr. 2015, pp. 53–61.
[7] V. Sydorov, M. Sakurada, and C. H. Lampert, “Deep Fisher kernels–end to end learning of the Fisher kernel GMM parameters,” in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., Jun. 2014, pp. 1402–1409.
[8] K. Simonyan, A. Vedaldi, and A. Zisserman, “Deep Fisher networks for large-scale image classification,” in Proc. Adv. Neural Inf. Process. Syst., 2013, pp. 163–171.
[9] F. Perronnin and D. Larlus, “Fisher vectors meet neural networks: A hybrid classification architecture,” in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., Jun. 2015, pp. 3743–3752.
[10] A. Krizhevsky, I. Sutskever, and G. E. Hinton, “Imagenet classification with deep convolutional neural networks,” in Proc. Adv. Neural Inf. Process. Syst., 2012, pp. 1097–1105.
[11] X. Zhou, K. Yu, T. Zhang, and T. S. Huang, “Image classification using super-vector coding of local image descriptors,” in Proc. Eur. Conf. Comput. Vis., Sep. 2010, pp. 141–154. Comput. Vis., Sep. 2010, pp. 141–154.
[12] X. Bai, C. Yan, P. Ren, L. Bai, and J. Zhou, “Discriminative sparse neighbor coding,” Multimedia Tools Appl., vol. 75, no. 7, pp. 4013– 4037, 2016.
[13] N. Inoue and K. Shinoda, “Fast coding of feature vectors using neighborto-neighbor search,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 38, no. 6, pp. 1160–1184, 2016.
[14] X. Li, M. Fang, and J. J. Zhang, “Projected transfer sparse coding for cross domain image representation,” J. Vis. Commun. Image Represent., vol. 33, pp. 265–272, Nov. 2015.
[15] S. R. Dubey, S. K. Singh, and R. K. Singh, “Local neighborhood based robust color occurrence descriptor for color image retrieval,” IET Image Process., vol. 9, no. 7, pp. 578–586, Jul. 2015.
[16] S. R. Dubey, S. K. Singh, and R. K. Singh, “Rotation and scale invariant hybrid image descriptor and retrieval,” Comput. Electr. Eng., vol. 46, pp. 288–302, Sep. 2015.
[17] G. H. Liu and J. Y. Yang, “Content-based image retrieval using color difference histogram,” Pattern Recognit., vol. 46, no. 1, pp. 188–198, 2013.
[18] W. T. Chu, C. H. Chen, and H. N. Hsu, “Color CENTRIST: Embedding color information in scene categorization,” J. Vis. Commun. Image Represent., vol. 25, no. 5, pp. 840–854, 2014.
[19] S. H. Lee, J. Y. Choi, Y. M. Ro, and K. N. Plataniotis, “Local color vector binary patterns from multichannel face images for face recognition,” IEEE Trans. Image Process., vol. 21, no. 4, pp. 2347–2353, Apr. 2012.
[20] Y. Xiao, J. Wu, and J. Yuan, “mCENTRIST: A multi-channel feature generation mechanism for scene categorization,” IEEE Trans. Image Process., vol. 23, no. 2, pp. 823–836, Feb. 2014.
[21] C. K. Heng, S. Yokomitsu, Y. Matsumoto, and H. Tamura, “Shrink boost for selecting multi-LBP histogram features in object detection,” in Proc. IEEE Int. Conf. Comput. Vis. Pattern Recognit., Jun. 2012, pp. 3250–3257.
[22] J. Y. Choi, K. N. Plataniotis, and Y. M. Ro, “Using color local binary pattern features for face recognition,” in Proc. 17th IEEE Int. Conf. Image Process. (ICIP), Sep. 2010, pp. 4541–4544.
[23] C. Zhu, C. E. Bichot, and L. Chen, “Multi-scale color local binary patterns for visual object classes recognition,” in Proc. IEEE Int. Conf. Pattern Recognit., Aug. 2010, pp. 3065–3068.
[24] C. Zhu, C.-E. Bichot, and L. Chen, “Image region description using orthogonal combination of local binary patterns enhanced with color information,” Pattern Recognit., vol. 46, no. 7, pp. 1949–1963, Jul. 2013.



10.22214/IJRASET

INDEX COPERNICUS
45.98

IMPACT FACTOR:
7.129

TOGETHER WE REACH THE GOAL
IMPACT FACTOR:
7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY