ISSN:0975-9646

Rekhil M Kumar et al, / (IJCSIT) International Journal of Computer Science and Information Technologies, Vol. 5 (6) , 2014, 7668-7673

A Survey on Image Feature Descriptors

Rekhil M Kumar
Dept.Of Computer And Information Science
College Of Engineering, Poonjar
Kottayam, Kerala, India

Sreekumar K
Dept.Of Computer And Information Science
College Of Engineering, Poonjar
Kottayam, Kerala, India

Abstract-Automatically assigning relevant text keywords to image is an important problem. Many algorithms have been proposed in the past decade and achieved good performance. Efforts have focused upon many other fields but properties of features have not been well investigated. In most cases, a group of features is selected in advance but important feature properties are not well used to feature selection. In this paper the performance of different features are compared, different combinations of features and a number of classification methods applied on the image annotation task, which gives insight into the features properties are also discussed.

General Terms
Computer vision, Image Processing.

Keywords
Automatic Image Annotation (AIA), Feature Extraction, Binary Descriptor, color Descriptors, Texture Descriptors.

1. INTRODUCTION

In the past decade, the number of images online and offline has increased dramatically. Many search engines retrieve images by text-based searching without using content information. The purpose of image annotation is to automatically assign relevant text keywords to any given image, reflecting its content properly.

The main task in Automatic Image Annotation (AIA) is to decrease the semantic gap between high level visual concepts and low level visual features. Social networking websites and image databases are in great need of systems such as AIA and its applications [7].

The problem of existing methods are some features are often preselected, but the properties of different features and combinations of feature are not well investigated in the image annotation task[9]. Second, these predefined features do not equally or positively contribute to the performance of annotation.

This paper presents a comparison between different image feature descriptors based on color, texture and shape to solve the feature related problems in the image annotation. Application and image representation scheme is analyzed using a number of descriptors.

2. REVIEW OF DESCRIPTORS

Recent techniques for AIA based image retrieval can be performed in two ways, the probabilistic modeling methods and the classification methods. The probabilistic modeling aim to develop a relevance model to represent the correlation between images and keywords. On the other hand, the (classification) model trains a separate classifier from visual features for each tag. These classifiers are used to predict particular tags for test image samples.

A feature is a metric or some quantifiable value which is used to describe an image at high level perspective. Features related to color, texture, shapes, color blobs, corners are contained in an image. The first step is to detect interest points in the image having the property of repeatability, means the ability to detect the same physical interest points under different viewing conditions, followed by the description calculation of the interest points. The feature needs to be unique i.e. if similar point is being described in two or more images then that point should have similar description and it should be of proper dimensions, a large descriptor will makes the computation longer. But if the descriptor is small then it may discard some useful information.

3. COLOR DESCRIPTORS

Color is a basic feature for image representation, and is invariant with respect to scaling, translation and rotation of an image [10].

3.1 Histograms

A histogram is the distribution of the number of pixels for an image. The number of elements in a histogram relates to the number of bits in each pixel of an image.

3.1.1 RGB histogram

The RGB histogram is a combination of three 1D histograms based on the R, G, and B channels of the RGB color space. This histogram having no invariance properties.

3.1.2 Opponent histogram

This is a combination of three 1D histograms of the channels of the opponent color space:

3.1.3 Hue histogram

In the HSV color space, the hue becomes unstable near the gray axis. The certainty of the hue and saturation are inversely proportional. Therefore, the hue histogram is made more robust by weighing each sample of the hue by its saturation. With respect to light intensity H color model is shift-invariant and scale-invariant .

3.1.4 rg histogram

In the normalized RGB color model, the chromaticity components r and g describe the color information in the image . Because of the normalization, r and g are scale-invariant, thus invariant to light intensity changes, shadows, and shading.

3.1.5 Transformed color distribution

An RGB histogram is not invariant to light changes. Scale-invariance and shift-invariance is achieved with respect to light intensity by the pixel value normalization. Because each channel is independently normalized, the descriptor is also normalized against changes in light color and arbitrary offsets.

3.2 Color Coherent Vector (CCV)

Color histogram does not discuss the spatial information of pixels thus similar color distribution for different images results. Here each histogram bin is partitioned of two types: coherent and incoherent. Coherent type contains pixel value belongs to a large informally colored region. Otherwise it is incoherent type. For each color in the image CCV represents this classification.

3.3 Color Moments and Moment Invariants

A color image corresponds to a function I defining RGB triplets for image positions (x, y): I : (x, y) → (R(x, y),G(x, y),B(x, y)). Considering RGB triplets as data points coming from a distribution, it is possible to define moments. color moments M^{abC}_{pq} :

$M^{abc}_{pq} = \int\int x^p y^q [IR(x, y)]^a [IG(x, y)]^b [IB(x, y)]^c dxdy.$

M^{abc}_{pq} is referred to as a generalized color moment of order p + q and degree a + b + c. Any spatial information do not contained in the moment of order 0, and moments of degree 0 do not contain any photometric information. The moment descriptions with order 0 are rotationally invariant, while higher orders are not. Generalized color moments up to the first order and the second degree are used.

3.3.1 Color moments

The descriptor uses all generalized color moments up to the second degree and the first order results in nine combinations for the degree:

M^{000}_{pq} ,M^{100}_{pq} , $^{M010}{}_{pq}$, $^{M001}{}_{pq}$, $M^{200}{}_{pq}$,$M^{110}{}_{pq}$, $^{M020}{}_{pq}$, $M^{011}{}_{pq}$,M^{002}_{pq} and $M^{101}{}_{pq}$

Combined with three possible combinations for the order. $M^{abc}{}_{00}$,$M^{abc}{}_{10}$ and $M^{abc}{}_{01}$, the color moment descriptor has 27 dimensions. These color moments only have shift-invariance.

3.3.2 Color moment invariants

Color moment invariants can be constructed from generalized color moments. To be comparable,the C02 invariants are considered which gives a total 24 color moment invariants.

3.4 Color SIFT Descriptors SIFT

It aimed to describe the local shape of a region by edge orientation histograms. The gradient of an image is possibly shift-invariant: taking the derivative cancels out offsets. Under changes in light intensity , i.e. intensity channel scaling , the direction of the gradient and relative gradient magnitude will be same. Because the SIFT descriptor is normalized, on the final descriptor,the gradient magnitude changes have no effect . The SIFT descriptor is not invariant to light color changes, because the R, G and B channels are combined to form the intensity channel.

3.4.1 HSV-SIFT

Bosch et al. compute SIFT descriptors over all three channels of the HSV color model. This gives 3x128 dimensions per descriptor, 128 per channel. As the H color model is scale-invariant and shift-invariant with respect to light intensity. However, due to the combination of the HSV channels, there is no invariance properties for the complte descriptor.

3.4.2 HueSIFT

Van de Weijer et al. introduce a concatenation of the hue histogram with the SIFT descriptor.By the comparison with HSV-SIFT, the weighed hue histogram addresses the instability of the hue near the grey axis. Because there are independant bins of the hue histogram,the hue channel periodicity for HueSIFT is addressed. Similar to the hue histogram, the HueSIFT descriptor is scale-invariant and shift-invariant.

3.4.3 OpponentSIFT

OpponentSIFT describes all the channels in the opponent color space using SIFT descriptors. The O3 channel information is equal to the intensity information,The other channels describe the color information in the image

3.4.4 C-SIFT

scale-invariant with respect to light intensity. By the color space definition, when taking the derivative the offset does not cancel out : it is not shift-invariant.

3.4.5 Rg SIFT

For this descriptor, descriptors are added for the r and g chromaticity components of the normalized RGB color model from , which is already scale-invariant.

Transformed color SIFT: For this descriptor, the same normalization is applied to the RGB channels as for the transformed color histogram. The SIFT descriptor is computed, For every normalized channel. The descriptor is scale-invariant, shift-invariant and invariant to shift and light color changes .

3.4.5 RGB-SIFT:

For the RGB-SIFT descriptor, SIFT descriptors are computed for every RGB channel . An important property of this descriptor, is that its descriptor values are equal to the transformed color SIFT descriptor, the RGB-SIFT and transformed color SIFT descriptors are equal.

The retrieval efficiency of color features investigated on the basis of recall and precision.

Most of the studies show that color histogram performs well compared than other descriptors when images have uniform color distribution. In most of the image categories color moments also results better performance. For images with widely scattered colors, CCV shows better comparison rate..The combination of color descriptors is better than individual color descriptors.

4. TEXTURE DESCRIPTORS

For browsing, searching and retrieval of images, texture can be a very useful feature. There is no formal definition for texture is known, but this descriptor provides measures of the properties such as smoothness, coarseness, and regularity. Statistical, structural and spectral methods are used to measure the texture properties of an image[14].One of the most known texture descriptors nowadays is GLCM.

4.1 GLCM(gray level co-occurrence matrix)

For motion estimation of images, this can be used to extract second order statistical texture features. The four features named as, Angular second moment, correlation, Inverse difference moment and Entropy are computed in GLCM extraction[17].

4.1.1 Angular Second Moment

Angular Second Moment is also known as Uniformity or Energy. It is the sum of squares of entries in the GLCM Angular Second Moment measures the image homogeneity. Angular Second Moment is high when image has very good homogeneity or when pixels are very similar.

4.1.2 Inverse Difference Moment

Inverse Difference Moment (IDM) is the local homogeneity. It is high when local gray level is uniform and inverse GLCM is high.

4.1.3 Entropy

Entropy shows the amount of information of the image that is needed for the image compression. Entropy measures the loss of information or message in a transmitted signal and also measures the image information.

4.1.4 Correlation

Correlation measures the linear dependency of grey levels of neighboring pixels.

When extracting the features of an image with GLCM approach ,at the time of RGB to GRAY level conversion the image compression time can be greatly reduced.

4.2 Haralick Texture Feature

The haralick textures are used for image classification. These features capture information about the patterns that emerge in patterns of texture. These kind of features are calculated by using co-occurrence matrix, which is computationally expensive.13 features are belongs to this category. Once the co occurrence matrix has been established calculation of these features will begin[20].The 13 haralick features are,

1) Energy
2) Correlation
3) Inertia
4) Entropy
5) Inverse Difference Moment
6) Sum Average
7) Sum Variance
8) Sum Entropy
9) Difference Average
10) Difference Variance
11) Difference Entropy
12) Information measure of correlation 1
13) Information measure of correlation 2

5. MPEG-7 VISUAL DESCRIPTORS

The MPEG-7 Visual Standard under development specifies content-based descriptors that allow users to measure similarity in images or video based on visual criteria, and can be used to efficiently identify, filter, or browse images or video based on visual content. More specifically, MPEG-7 specifies color, texture, object shape, global motion, or object motion features for this purpose

5.1 Visual color descriptors

Color is the most widely used visual feature in image and video retrieval. Color features are robust to changes in the background colors and are independent of orientation and size of image and can be used for defining still images and video content.

5.1.1 Color Spaces

To allow interoperability between various color descriptors, normative color spaces are constrained to hue-saturation-value (HSV) and hue-min-max-diff (HMMD). HSV is a well-known color space mostly used in image applications. HMMD is a new color space defined by MPEG and is only used in the color structure descriptor (CSD) explained below.

5.1.2 Scalable Color Descriptor (SCD)

The MPEG-7 SCD is a color histogram encoded by a Haar transform. It uses the HSV colors space uniformly quantized to 255 bins.

5.1.3 Dominant Color Descriptor

This color descriptor aims to describe global as well as local spatial color distribution in images for high-speed retrieval and browsing. In contrast to the Color Histogram method, this arrives at more compact representation—at the expense of lower performance in some applications. The descriptor consists of the representative colors, their percentages in a region, spatial coherency of the color, and color variance.

5.1.4 Color Layout Descriptor(CLD)

This descriptor is designed to describe spatial distribution of color in an arbitrarily-shaped region. Color distribution in each region can be described using the Dominant Color Descriptor above.

5.1.5 CSD (color structure descriptor)

The main purpose of the CSD is to express local color features in images.Group-of-Frames/Group-of-Pictures (GoF/GoP) Color Descriptor: The descriptor defines a structure required for representing color features of a collection of similar frames or video frames by means of the SCD

5.2 Visual texture descriptors

Texture refers [11] to the visual patterns that have properties of homogeneity or not, that result from the presence of multiple colors or intensities in the image. It is a property of virtually any surface, including, bricks, trees, hair, fabric and cloud. It contains important structural information of surfaces and their relationship to the surrounding environment.

5.2.1 Texture Browsing Descriptor

To characterize texture regularity (2bits) , directionality(3bits*2) and coarseness(2 bits*2), this compact descriptor requires only 12 bits. A texture may have more than one dominant direction and associated scale. For this reason, the specification allows a maximum of two different directions and coarseness values[15].The computation of this descriptor is as ,the image is filtered using a bank of scale and orientation selective band-pass filters and the filtered outputs are then used to compute the texture browsing descriptor components

5.2.2 Homogenous Texture Descriptor

This describes coarseness, a regularity and directionality of patterns in images and is most suitable for a quantitative characterization of texture that has homogenous properties. It can be used for similarity image-to-image matching for texture image databases[16].

5.2.3 Non-Homogenous Texture Descriptor (Edge Histogram)

In order to provide descriptions for non homogenous texture images, MPEG-7 defined an Edge Histogram Descriptor. This descriptor captures spatial distribution of edges, somewhat in the same spirit as the Color Layout Descriptor. This is scale invariant, rotation-sensitive and rotation-invariant matching are also supported. It is also very compact because using 3 bins each histogram bin is non uniformly quantized, results in a 240 bits descriptor size[16].

5.3 visual shape descriptors

In image data-base applications, the shape of image objects provides a useful hint for similarity matching. For image retrieval the shape descriptor wants to be invariant to scaling, rotation and translation [9].

5.3.1 3-D Shape Descriptor—Shape Spectrum

It can be described as the histogram of a shape index, computed over the entire 3-D surface. The shape index itself computes vexity of each local 3-D surface. Histograms with 100 bins each quantized by 12 bits are used.

5.3.2 Region-Based Descriptor—Art:

The Region- Based Descriptor ART (Angular Radial Transformation) belongs to the class of moment invariants methods for shape description. This descriptor is well for shapes that can be best described by shape regions rather than contours. The idea behind moment invariants is to use region-based moments as the shape feature that are invariant to transformations,

5.3.3 Contour-Based Shape Descriptor

Objects for which shape features are best expressed by contour information can be described using the MPEG-7

5.3.4 Contour-Based Descriptor.

This descriptor is based on curvature scale-space (CCS) representations of contours and also includes eccentricity and circularity values of the original and filtered contours.

6. FREQUENCY DOMAIN DESCRIPTORS

It is having lower computational costs. The idea behind binary descriptors is that each bit in the descriptor is independent and the Hamming distance can be used as similarity measure instead of, e.g., the Euclidean distance .The four most recent and promising binary feature descriptors are (1) Binary Robust Independent Elementary Feature (BRIEF), (2) Oriented Fast and Rotated BRIEF (ORB) , (3) Binary Robust Invariant Scalable Key points (BRISK) and (4) Fast Retina Key point (FREAK) .

6.1 Scale Invariant Feature Transform (SIFT)

SIFT[18] was originally introduced by Lowe as combination of a DoG interest region detector and a corresponding feature descriptor. However, both components have since then also been used in isolation. This descriptor aims to achieve robustness to lighting variations and small positional shifts by encoding the image information in a localized set of gradient orientation histograms.

6.2 SURF Descriptor/Detector

SURF ("Speeded-Up Robust Features")[19] approach, which is an effective alternative to SIFT. SURF combines its own gradient orientation based feature descriptor with a Hessian-Laplace region detector. For the internal computations, it uses 2D box filters ("Haar wavelets"). These box filters approximate the effects of the derivative filter kernels, and can be evaluated using integral images.

6.3 Maximally Stable Extremal Regions (MSER)

In images the MSER is used for the blob detection. The algorithm for MSER extracts co-variant regions from an image ,this is known as MSER's. Thus it is a stable connected component of some gray level sets of the image. The MSER extraction follows the steps

- Sweep threshold of intensity from black to white, performing a simple luminance thresholding of the image
- Extract connected components ("*Extremal Regions*")
- Find a threshold when an extremal region is "Maximally Stable", i.e. local minimum of the relative growth of its square. Due to the discrete nature of the image, the region below / above may be coincident with the actual region, in which case the region is still deemed maximal.
- Approximate a region with an ellipse (*this step is optional*)
- Keep those regions descriptors as features However

An external region which is maximally stable might also be rejected, if

- it is too big (there is a parameter Max Area);
- it is too small (there is a parameter Min Area);
- it is too unstable (there is a parameter Max Variation);
- it is too similar to its parent MSER

MSER properties:

- MSER performs well on images containing homogeneous regions with distinctive boundaries.
- MSER works well for small regions
- MSER doesn't work well with images with any motion blur
- Good repeatability
- Affine invariant
- A smart implementation makes it one of the fastest region detectors

6.4 ORB(oriented fast and rotated brief)

In the research paper "ORB**:** an efficient alternative to SIFT or SURF" written by Ethan Rublee Vincent Rabaud Kurt Konolige Gary [3] a very fast binary descriptor based on BRIEF, called ORB ,is proposed which is rotation invariant and resistant to noise.

The proposed feature builds on the well-known FAST key point detector and the recently-developed BRIEF descriptor; for this reason we call it ORB (Oriented fast and rotated brief) .Both these techniques are attractive because of their good performance and low cost. In this paper, They address several limitations of these techniques vis-a-vis

SIFT, most notably the lack of rotational invariance in BRIEF.

The main contributions of this research are.

- The addition of a fast and accurate orientation component to FAST.
- The efficient computation of oriented BRIEF features.
- Analysis of variance and correlation of oriented BRIEF features.
- A learning method for de-correlating BRIEF features under rotational invariance, leading to better performance in nearest-neighbor applications.

It evaluates the combination of oFAST and rBRIEF, which we call ORB, using two datasets: images with synthetic in-plane rotation and added Gaussian noise, and a real-world dataset of textured planar images captured from different viewpoints.ORB is relatively immune to Gaussian image noise, unlike SIFT. If we plot the inliers performance vs. noise, SIFT exhibits a steady drop of 10% with each additional noise increment of 5. ORB also drops, but at a much lower rate.

6.5 BRIEF

BRIEF [4] is a recent feature descriptor that performs simple binary tests between pixels in smoothed image regions. In many respects like blur robustness to lighting, and perspective distortion Its performance is similar to SIFT. However, it is very sensitive to in-plane rotation.

6.6 BRISK (Binary Robust Invariant Scalable Key points)

BRIEF [4] is a recent feature descriptor that uses simple binary tests between pixels in a smoothed image patch. Its performance is similar to SIFT in many respects, including robustness to lighting, blur, and perspective distortion. However, it is very sensitive to in-plane rotation.

BRIEF grew out of research that uses binary tests to train a set of classification trees [5]. Once trained on a set of 500 or so typical key points, the trees can be used to return a signature for any arbitrary key point

The classic method for finding uncorrelated tests is Principal Component Analysis; for example, it has been shown that PCA for SIFT can help remove a large amount of redundant information. However, the space of possible binary tests is too big to perform PCA and an exhaustive search is used instead.

Visual vocabulary methods use offline clustering to find exemplars that are uncorrelated and can be used in matching. These techniques might also be useful in finding uncorrelated binary tests. The closest system to ORB is , which proposes a multi-scale Harris key point and oriented patch descriptor. This descriptor is used for image stitching, and shows good rotational and scale invariance.

6.7 FREAK (Fast Retina Key Point*)*

Alexandre Alahi, Raphael Ortiz, Pierre Vandergheynst in their paper "FREAK"[6], discussing about novel key point descriptor inspired by the human visual system and more precisely the retina, coined Fast Retina Key point (FREAK). A cascade of binary strings is computed by efficiently comparing image intensities over a retinal sampling pattern.

Many sampling grids are possible to compare pairs of pixel intensities. BRIEF and ORB use random pairs. BRISK uses a circular pattern where points are equally spaced on circles concentric. The testing environments rank FREAK as the most robust to all the tested image deformation. Surprisingly, SIFT is the worst descriptor in the first testing environment similar to what has been shown in BRISK. FREAK is faster than BRISK but BRISK is two orders of magnitude faster than SIFT and SURF.

The two main stages proposed in this paper is Training and Query part. Images are first fed into the SURF function from training set. This will extract the interest points from each image. These points will then clustered into k clusters by k-means algorithm, Euclidean distance, with respect to their descriptors. In query part when a user submitted a query image, using SURF algorithm interest points and descriptors will be extracted.

In "evaluation of binary key point descriptors" by Dagmawi Bekele, Michael Teutschy and Tobias Schucherty[1]:- have presented an experimental evaluation of binary key point descriptors on Stanford Mobile Visual Search and Oxford data set. ,first step in the evaluation is detecting key points in both the reference and query images. It uses a Ratio Test and Brute force matcher for feature matching in the second step. The next step in the evaluation is the RANdom Sample Consensus (RANSAC).

From evaluation results BRISK is recommended as the best binary key point descriptor yielding best matches which is comparable with that of SIFT .But BRISK needs significantly more computation effort compared to BRIEF and ORB . Also FREAK descriptors are faster to compute compared to BRISK, while simultaneously demands less memory load. We can conclude, that on the SMVS data set BRISK yields best results, and FREAK gives less performance but faster computation.

Speeded- Up Robust Features (SURF) combined with Bag-of-Visual- Words (BoVW) are used in the method proposed by Chandrika L in "Implementation Image Retrieval and Classification with SURF Technique"[2].

7. CONCLUSION

This paper presents a comparative study of global and local feature descriptors. The comparative study considers both theoretical and experimental aspects, and checking for efficiency and effectiveness. Overall, the semantic gap continues to be a big challenge for image feature descriptors, especially in the context of information retrieval.

REFERENCE

[1] Evaluation of binary key point descriptors by Dagmawi Bekele, Michael Teutsch, Tobias Schuchert: Karlsruhe Institute of Technology, Karlsruhe, Germany Fraunhofer Institute of Optronics, System Technologies and Image Exploitation, Karlsruhe, Germany.

[2] Implementation Image Retrieval and Classification with SURF Technique By Chandrika L

[3] ORB: an efficient alternative to SIFT or SURF" written **by** Ethan Rublee Vincent Rabaud Kurt Konolige Gary

[4] M.Calonder, V. Lepetit, C. Strecha, and P. Fua. Brief: Binary robust independent elementary features. In *In European Conference on Computer Vision*, 2010

[5] M. Calonder, V. Lepetit, and P. Fua. Key point signatures for fast learning and recognition. In *European Conference on Computer Vision*, 2008

[6] FREAK By Alexandre Alahi, Raphael Ortiz, Pierre Vandergheynst, Ecole Polytechnique F´ed´erale de Lausanne (EPFL), Switzerland

[7] Automatic Image Annotation Using Synthesis of Complementary Features, by Sreekumar k, Anjusha B, Rahul Nair, Department of Computer Science College of Engineering Poonjar Kottayam, Kerala, India

[8] Automatic Image Annotation using SURF Features. Tuhin Shukla School of Information Technology, Rajiv Gandhi Proudyogiki Vishwavidyalaya, Bhopal, Madhya Pradesh, India

[9] Automatic Image Annotation Using Group Sparsity. Shaoting Zhang†, Junzhou Huang†, Yuchi Huang†, Yang Yu†, Hongsheng Li§, Dimitris N. Metaxas† †Department of Computer Science, Rutgers,University, Piscataway, NJ, 08854Department of Computer Science and Engineering, Lehigh University, Bethlehem, PA,

[10] MPEG-7 Visual Shape Descriptors Miroslaw Bober ,ieee transactions on circuits and systems for video technology, vol. 11, no. 6, june 2001

[11] Color and Texture Descriptors.B. S. Manjunath*, Member, IEEE*, Jens-Rainer Ohm*, Member, IEEE*, Vinod V. Vasudevan*, Member, IEEE*, and Akio Yamada. ieee transactions on circuits and systems for video technology, vol. 11, no. 6, june 2001

[12] Comparative study of global color and texture descriptors for web image retrieval Otávio A.B. Penatti a,□, Eduardo Valle a,b, Ricardo da S. Torres. www.elsevier.com/ locate/ jvci

[13] BRISK: Binary Robust Invariant Scalable Key points, Stefan Leutenegger, Margarita Chli and, Roland Y.

[14] Content Based Image Retrieval using Color and Texture Manimala Singha* and K.Hemachandran$ Dept. of Computer Science, Assam University, Silchar India.

[15] B. S. Manjunath, P. Wu, S. Newsam, and H. Shin, "A texture descriptor for browsing and image retrieval," ***Int. Commun. J.***, vol. 16, pp. 33–43,Sept. 2000

[16] The MPEG-7 Visual Standard for Content Description—An Overview Thomas Sikora*, Senior Member, IEEE*

[17] Image Texture Feature Extraction using GLCM Approch by P. Mohanaiah*, P. Sathyanarayana, L. GuruKumar Professor, Dept. of E.C.E, N.B.K.R.IST, Vidyanagar, Nellore, India Professor, Dept. of E.C.E, S.V University Tirupati, India Asst.Professor, Dept. of E.C.E, N.B.K.R.IST.

[18] David G. Lowe, "Object recognition from local scale-invariant features," *Int. Conf. on Computer Vision,* Corfu, Greece (September 1999), pp. 1150-1157

[19] Dalal, N. and Triggs, B. , "Histograms of oriented gradients for human detection". *Int. Conf. on Computer Vision & Pattern Recognition*, 2005, volume 2, pages 886–893.

[20] Fast calculation of haralick texture features Eizan Miyamoto and Thomas Merryman Jr.