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Detection and Recognition of Outdoor Objects based on SIFT Features

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Abstract: Object detection and recognition is very essential for visually impaired to survive at indoor and outdoor environments. The objective of this paper is to detect and recognize the outdoor objects. In an effective method is proposed and implemented for the extraction of the objects from the outdoor environment automatically. The outdoor objects are detected from the real-time outdoor images. The outdoor objects are detected using Haar-like features and AdaBoost classifier. SIFT features are extracted from the detected objects and classified using Support Vector Machine. The experimental results reveals that the detection and recognition rate for real-time outdoor object using SIFT with SVM is 91.10%.

Keywords: object detection, AdaBoost Classifier, Haar-like feature, Support Vector Machine (SVM) classifier, Scale Invariant Feature Transform (SIFT).

I. INTRODUCTION

Detection and recognition is difficult to recognize by the visually impaired. The major issues to detect and recognize the outdoor objects were poor lightening, occluded objects, different orientation, colour fading effect. To overcome these issues the following techniques were used. Number of feature extraction point chosen from a given image is depends on the complexity of an image, but the feature extracted from each point is seven. The outdoor objects can be detected by using the Haar -like features and classified by the AdaBoost classifier. Then, the outdoor objects can be recognized by using the SIFT feature with SVM classifiers. The proposed system is then detects and recognizes the outdoor objects through these above processes.

A. Outdoor Scenes

Outdoor scenes consists of several things both manmade and natural objects which are present in the outdoor environment like tree, car, bus, road, buildings, dam, etc. It is more difficult to identify the objects present in outside environment. The following figure (see Figure 1), as the examples for the outdoor scenes.

Figure 1. Outdoor Scenes

B. Outline of Work

The detection and recognition of outdoor objects system consists of different modules they were described in the upcoming sections. Pre-processing is described in section 2. Detection of outdoor objects is described in section 3. Recognition of outdoor objects is described in section 4. Experimental results are described in section 5. Performance measure is described in section 6. Conclusion is provided in section 7. Outdoor scene recognition will be described as a future enhancement process.

The figure (see Figure 2) shows the block diagram of the proposed system.

Block Diagram

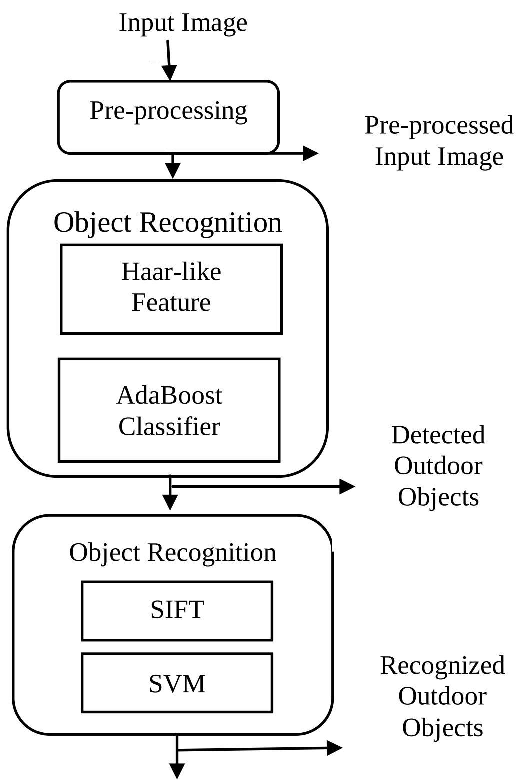

Figure2. Block diagram of the proposed system

The block diagram of this work consists of 4 modules as described above diagram (see Figure 2).

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II. PRE-PROCESSING

A. Log Polar Image

Log-polar pictures [1] are specified devote a high sight within the centre of the sphere of read, so lost objects will be perceived with excellent quality, as a result of the resolution decreases exponentially with eccentricity, the dimensions of the log-polar image is tiny.

B. Gray Scale Conversion

The input image is regenerate from colour image to the gray scale image. It is used to make the process easy and efficient using the basic gray scale conversion equation.

C. Resize

Resize the input image to a standard form 320 by 240 dimension. It is used to reduce the memory size and the time complexity.

III. DETECTION OF OUTDOOR OBJECTS

In object detection, the outdoor objects were detected by using two techniques, one for extract features from the input image and another one is to classify or to draw a bounding box over the object in an image.

A. Haar-Like Features Extraction Technique

Haar-like options [2] are digital imaging options that are accustomed discover objects. Viola and Jones tailored the concept of victimization Haar wavelets and developed the alleged Haar-like options. The Haar-like feature consists of black and white parallelogram regions. The value of a Haar-like feature is the difference between the total of the Gray picture element value within the black and white rectangular regions. After Haar-like feature applied to the raw pixels, classification is easier. Haar-like feature is applied to the bounding-box image as shown in the equation below,

F(x) = Sum $_{\text{black rectangle}}$ (Gray pixel level) - Sum $_{\text{white rectangle}}$ (Gray pixel level)

There are five basic Haar-like features to detect and extract the image features, they were shown below (see Figure 3).

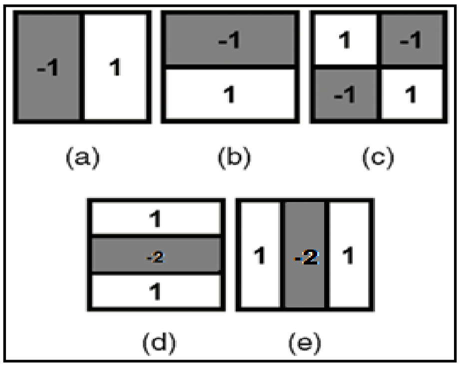

Figure 3. Basic Haar-like features

The above Figure 3, shows that, the Haar feature A detects the horizontal variation of pixels in the images. Haar feature B detects the vertical variation of pixels in the images. Haar feature C detects the diagonal variation of pixels in the images. Haar feature D detects the vertical variation of pixels in the images. Haar feature E detects the horizontal changes.

B. AdaBoost Classifier

The steps that are involved in the detection of objects in an image:

Input:

The training set (x_1,y_1), (x_n, y_n), where x_i is the data of the i^{th} example, and $y_i \in$ Y= {-1, 1}. Number of learning rounds T.

PROCESS:

1. Initialize the weights, $\omega_{1,i} = \frac{1}{n}$ for each example (x_i,y_i).
2. **for t=1, ... , T do**
3. Train a weak learner h_t using the weights $\omega_{t,i}$.
4. Get the weak learner with error,

$$\epsilon_t = \sum_{i=0}^{n} \omega_{t,i} \| h_t(x_i) - y_i \|^2 \qquad \textbf{(3.2)}$$

5. If $\in_t > 0.5$ then break
6. Choose $\propto_t = \frac{1}{2} ln(\frac{1-\epsilon_t}{\epsilon_t})$
7. Update the weights

$$\omega_{t,i} = \omega_{t,i} * \begin{cases} e^{-\propto_t}, if\ h_t(x_i) = y_i \\ e^{\propto_t}\ , if\ h_t(x_i) \neq y_i \end{cases} \qquad \textbf{(3.3)}$$

8. Normalize the weights

$$\omega_{t+1,i} = \frac{\omega_{t,i}}{\sum_{i=1}^{n} \omega_{t,i}} \qquad \textbf{(3.4)}$$

where the standardization may be expressed by a normalized issue Z_t, so that all $\omega_{t+1,i}$ can keep a chance distribution.

9. **end for**

Output:

The final object window (i.e., strong classifier):

$$H(x) = \begin{cases} 1, & if \sum_{t=1}^{T} \propto_t h_t(x) \geq \frac{1}{2} \sum_{t=1}^{T} \propto_t \\ -1, & Otherwise \end{cases}$$

AdaBoost (Adaptive Boost) [1] is an iterative iteratively ordering calculation to build a strong classifier utilizing just a preparation set and it is a weak learning calculation. It changes the weak classifiers into a strong classifier. A weak classifier with the base arrangement mistake is chosen by the examining calculation at every emphasis.

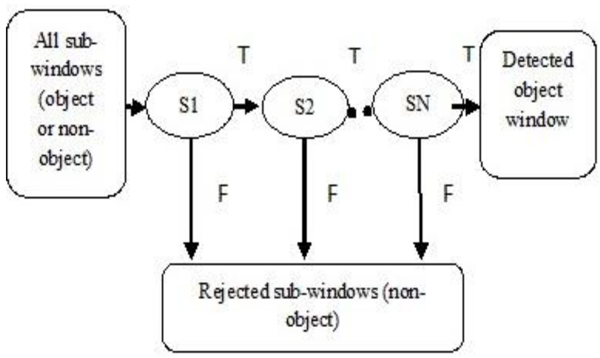

Figure4. Structure of AdaBoost classifier

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Figure 4 shows the structure of the AdaBoost classifier. In AdaBoost classifier, positive samples (i.e., object sub-window) only passed or load to the next stage, negative features (i.e., non-object sub-window) were just rejected in each stage.

In train cascade object detector perform, the cascade classifier coaching needs a group of positive samples and a group of negative pictures. This work has a tendency to offer a group of positive pictures with regions of interest specific to be used as positive samples. This work have a tendency to additionally should offer a group of negative pictures from that they can perform and generates negative samples mechanically. Work got to line the amount of stages, feature kind, and different perform parameters to realize acceptable detector accuracy. Figure 4, shows associate AdaBoost classifier to discover objects and non-object windows. Positive samples are pictures that contain outside objects. The positive samples should be marked out for classifier coaching. Negative samples are non-object windows. These pictures should not contain object representations. Positive samples are images which contains outdoor objects. The positive examples must be set apart out for classifier preparing. Negative examples are non-object pictures. Negative specimens are taken from self-assertive pictures. These pictures must not contain protest representations.

C. Training and Testing of Outdoor Objects

In outdoor object detection, there are totally 90 outdoor object images are taken. Each image undergoes training and testing using AdaBoost classifier algorithm. Based on number of iterations, thus the training stage and False alarm rate is getting varied for every input image given to the classifier.

The various outdoor object images are taken such as market, vehicle and park. Among the 90 outdoor object images only 60 images are detected accurately. The cropped view of outdoor objects after detection is shown in figure (see Figure 6).

Figure 5(a). Input image 5(b) Objects detected using bounding boxes

Bounding boxes are used to represent the detected outdoor objects from the given input image. Figure 5 a) shows the real-time input image and the market is detected using bounding box which is shown in Figure 5 b).

Figure 6. Cropped view of outdoor objecs

IV. RECOGNITION OF OUTDOOR OBJECTS

Recognition of outdoor objects from the input image can be handled with the help of different kinds of feature extractors and classifiers. In this work, few techniques were implemented to detect and recognize the outdoor objects effectively. In the upcoming section IV describes about the techniques which were implemented to detect and recognize the outdoor objects effectively. In the upcoming section 4 describes about the techniques which were implemented in this proposed work. After pre processing the image, techniques were applied to extract the specified samples from the image and to classify the image through the extracted samples.

A. Feature Extraction Techniques

In image process, feature extraction could be a special sort of spatiality reduction. once the computer file to associate degree rule is just too massive to be processed and it's suspected to be terribly redundant, then the computer file are remodeled into a reduced illustration set of options (also named options vector). If the options extracted square measure rigorously chosen it's expected that the options set can extract the relevant info from the computer file so as to perform the specified task victimization this reduced illustration rather than the total size input.

B. Scale Invariant Feature Transform

Scale-Invariant Feature Transform (SIFT) [4] is associate algorithmic program is to discover and describe native options in pictures. The algorithmic program was printed by David Lowe. SIFT will robustly establish objects even among litter and beneath partial occlusion, as a result of the SIFT feature descriptor is invariant to uniform scaling, orientation, and part invariant to affine distortion and illumination changes. The SIFT descriptor comprised a way for police investigation interest purposes from a grey-level image at that statistics of native gradient directions of image intensities were accumulated to convey a summarizing description of the native image structures in an exceedingly native neighborhood around every interest point. The four real stages to catch the peculiarity portrayal of a picture are:

1. Detection of scale-space Extrema
2. Key point localization
3. Orientation assignment
4. Key point descriptor

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1. Detection of scale-space extrema

The first stage is to construct a mathematician "scale space" perform from the input image. This is often fashioned by convolution of the first image with mathematician functions of variable widths. The size house of a picture is outlined as a perform L(x, y, σ) this is often created from the convolution of a variable-scale mathematician, G(x, y, σ) with Associate in Nursing input image, I(x, y).

$$L(x, y, \sigma) = G(x, y, \sigma)^* I(x, y) \text{-------------------------} (4.1)$$

Where ∗ is that the convolution operation in x and y, and

$$G(x, y, \sigma) = \frac{1}{2\pi\sigma 2} e^{-(x2+y2)/2\sigma 2} \text{---------------------} (4.2)$$

To expeditiously observe stable key point locations in scale house, Lowe projected exploitation scale-space extrema within the difference-of-Gaussian operate convolved with the image, D(x, y, σ), which might be computed from the distinction of 2 near scales separated by a continuing increasing issue k:

$$DoG(x, y, \sigma) = (G(x, y, k\sigma) - G(x, y, \sigma)) * I(x, y)$$
$$= L(x, y, k\sigma) - L(x, y, \sigma) \text{----------------------} (4.3)$$

There is variety of reasons for selecting this performs. First, it's a very economical perform to cipher, because the ironed pictures, L, ought to be computed in any case for scale area feature description, and DoG will thus be computed by easy image subtraction. To notice the native maxima and minima of DoG(x, y, σ) every purpose is compared with its eight neighbours at a similar scale, and its nine neighbours up and down one scale.

2. Key point localization

This stage makes an attempt to eliminate some points from the candidate list of key points by finding those who have low distinction or square measure poorly localized on a grip. The worth of the key points within the DoG pyramid at the extrema is given by:

$$D(z) = D + \frac{1}{2}\frac{\partial D^{-1}}{\partial x} z \text{----------------------------------} (4.4)$$

If the operation price at z is below a threshold price this time is excluded. To eliminate poorly localized extrema we tend to use the very fact that within these cases there's an outsized principle curvature across the sting however a tiny low curvature within the perpendicular direction in the distinction of Gaussian operation.

A 2x2 Hessian matrix, H, computed at the situation and scale of the key points is employed to seek out the curvature. With these formulas, the quantitative relation of principal curvature may be checked expeditiously.

$$H = \begin{bmatrix} D_{xx} & D_{xy} \\ D_{xy} & D_{yy} \end{bmatrix} \text{--} (4.5)$$

3. Orientation assignment

This step aims to assign an even orientation to the key points supported native image properties. An orientation bar graph is created from the gradient orientations of sample points inside a section round the key points. A 16x16 sq. is chosen during this implementation. The orientation bar graph has thirty six bins covering the 360 degree vary of orientations. The gradient magnitude, m(x, y), and orientation, θ(x, y), square measure pre-computed mistreatment pixel variations:

m(x, y) =

$$\sqrt{(L(x+1, y) - L(x-1, y))2 + (L(x, y+1) - L(x, y-1))2} \text{--} (4.6)$$

$$\theta(x, y) = \tan^{-1}\left(\frac{L(x, y+1) - L(x, y-1)}{L(x+1, y) - L(x-1, y)}\right) \text{-------------} (4.7)$$

Here, a descriptor is computed for the native image region that's as distinctive as attainable at every key point. The image gradient magnitudes and orientations were sampled round the key point location. A Gaussian coefficient operate with σ associated with the size of the key point is employed to assign a weight to the magnitude. Here it uses associate σ up to one half the breadth of the descriptor window during this implementation.

It is used to attain orientation unchangeable, the coordinates of the descriptor and also the gradient orientations area unit turned relative to the key point orientation. This method is indicated in Figure 7. Building key points, a 16x16 sample array is computed and a bar graph with eight bins is employed. Thus a descriptor contains 16x16x8 components in total.

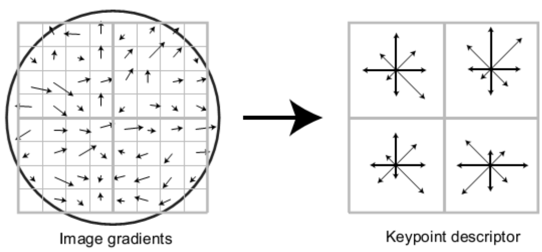

Figure7. Building key points

These square measure weighted by a Gaussian window, indicated by the Overlaid circle (log polar image). The image gradients square measure additional to associate degree orientation histogram. Every histogram embrace 8 directions indicated by the arrows and is computed from 4x4 Sub regions. The length of every arrow corresponds to the total of the gradient magnitudes close to that direction among the region. The key points of outside object square measure shown in Figure 8.

Figure8. Key points of Outdoor Objects

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4. Key point descriptor
Each Key points are described with the vectors is considered as features of the key point.

C. RECOGNITION OF OUTDOOR OBJECTS USING SVM
Support vector machine (SVM) [2] [3] [4] depends on the rule of basic danger diminishment (SRM). Like RBFNN, Support vector machines might be utilized for example order and nonlinear relapse SVM builds a linear model to assess the choice operation misuse non-straight classification limits upheld support vectors. In the event that the data zone unit sprightly isolated, SVM trains direct machines for a best hyper plane that isolates the data while not blunder and into the most separation between the hyper plane range units known as support vectors. Figure 10, demonstrates that the SVM maps the info designs into the following dimensional component zone through some nonlinear mapping picked from the earlier. A straight call surface is then made a mid this high dimensional component region. In this manner, SVM could be a straight classifier inside of the parameter territory; be that as it may it turns into a nonlinear classifier as an after-effect of the nonlinear mapping of the range of the information designs into the high dimensional element region.
Support vector machine (SVM) might be utilized for grouping the acquired data. SVM territory unit a gathering of associated regulated learning technique utilized for order and relapse. They have a place with a group of summed up straight classifiers. Permit us to indicate a component vector (termed as pattern) by $x=(x_1, x_2, \cdot, x_n)$ and its class name by y such y =. Hence, consider the matter of isolating the arrangement of n-preparing designs into 2 classes.

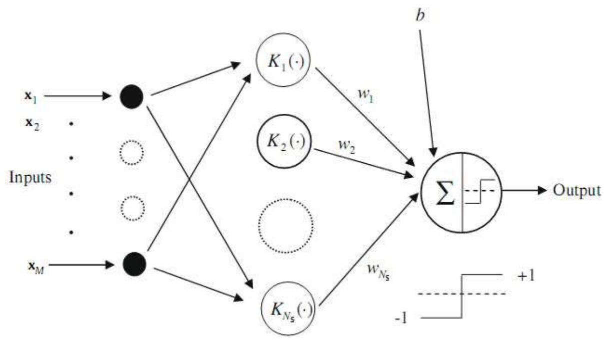


Figure9. Architecture of SVM Classifier

A choice operation g(x) that might appropriately order associate in arranging data design x that is not basically from the training set.

$$g(x) = \omega^t x + b \text{---} 4.8$$

Such that $g(x_i) \geq 0$ for $y_i = +1$ and $g(x_i) < 0$ for $y_i = -1$. As it were, preparing tests from the two diverse classes are isolated by the hyper plane $g(x) = \omega^t x + b = 0$. SVM finds the hyper plane that causes the biggest partition between the choice capacity values from the two classes. Numerically, this hyper plane can be found by minimizing the accompanying cost capacity:

$$j(\omega) = \omega^t \omega \text{---} 4.9$$

For the **directly distinguishable information**, the choice tenets characterized by an ideal hyper-plane isolating the parallel choice classes are given in the accompanying mathematical statement as far as the support vectors.

$$Y = \text{sign}\left(\sum_{i=1}^{i=N} y_i (xx_i) + b\right) \text{------------------------} 4.10$$

Where Y is the outcome, y_i is the class estimation of the preparation sample x_i and speaks to the internal item. The vector relates to an information and the vectors x_i, i = 1. . .Ns, are the support vectors.

$$Y = \text{sign}\left(\sum_{i=1}^{i=N} y_i\, k(xx_i) + b\right) \text{----------------------} 4.11$$

The support vectors are (just as) near hyper-plane. The bolster vectors are preparing tests that categorize the ideal isolating hyper-plane and are the most troublesome examples to group.

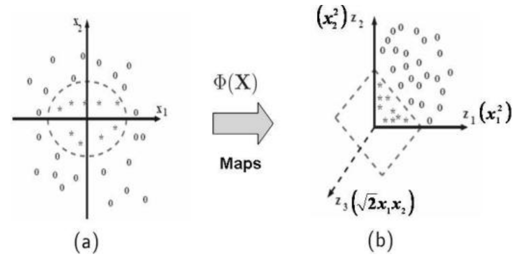
SVM by and large applies to straight limits. For the situation where a straight limit is unseemly SVM can delineate info vector into a high dimensional component space. By picking a non-direct mapping, the SVM develops an ideal isolating hyper-plane in this higher dimensional space, as appeared in Figure 12. The capacity is characterized as the bit capacity for creating the inward items to develop machines with various sorts of non-direct choice surfaces in the data space.

$$K(x, x_i) = \Phi(x).\ \Phi(x_i) \text{---------------------------------} 4.12$$

The kernel perform is also any of the bilateral functions that satisfy the Mercer's Conditions. There are many SVM kernel functions as given in Table 1, forms of SVM scalar product kernels.

Table1. Types of SVM Inner Product Kernels

Types of Kernels	Inner Product Kernels $k(x^T, x_i)$	Details
Polynomial	$(x^T x_i + 1)^p$	Where x is input patterns, x_i is support vectors, σ^2 is variance. $1 \leq i \leq N_s$, N_s is number of support vectors, β_0, β_1 are constant values. P is degree of the polynomial.
Gaussian	$\text{Exp}[-\|\|x^T - x_i\|\|^2 / 2\sigma^2]$	
Sigmoid	$\text{Tan h}(\beta 0 x^T x_i + \beta 1)$	



(a) Nonlinear problem. (b) Linear problem.
Figure10. An example for SVM kernel function

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V. EXPERIMENTAL RESULTS

Performance efficiency of the outdoor object recognition using SIFT with SVM were measured for different kinds of outdoor objects. Three categories of outdoor objects are considered such as vegetables, children's park equipment and vehicles. These 20 outdoor object images were used to train (per category) and 10 outdoor object images were used to test (per category). SIFT features were extracted from each and every outdoor objects and through SVM classifier, new outdoor objects were recognized. The accuracy rate of SIFT with SVM is 91.10%. Figure given below shows the GUI screen of SIFT with SVM (see Figure 11). Table 3 given here denotes the confusion matrix of outdoor objects in real time with the help of SIFT with SVM.

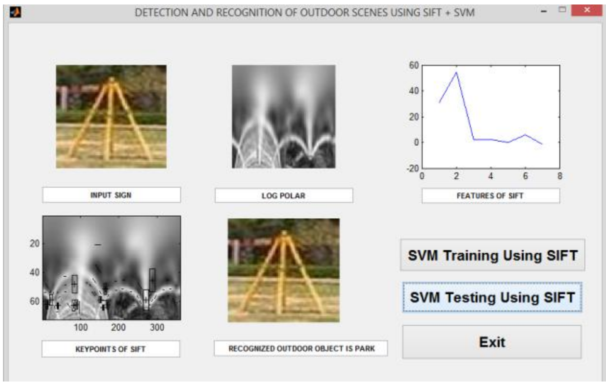

Figure11. GUI screen of SIFT with SVM

Table3. Confusion matrix for recognition of outdoor objects in real-time with SIFT using SVM

Object Name	True positive	False Positive	False Negative	True Negative
Market	9	1	1	19
Vehicles	8	2	2	18
Park	9	1	1	19

The rightness of a sort will be assessed by registering the amount of appropriately perceived class [2] samples (true positives), the amount of legitimately perceived illustrations that don't have a place with the classification (true negatives), and cases that either were inaccurately doled out to the classification (false positives) or that weren't perceived as class cases (false negatives).

1) Precision

Precision may be alive of the accuracy only if a selected category has been foreseen. It's outlined by:

$$\text{Precision} = \frac{\text{true positive}}{\text{true positive} + \text{false positive}} \text{ -------------- } (5.1)$$

2) Recall

Recall may be alive of the power of a prediction model to pick instances of a definite category from an information set. It's outlined by the formula:

$$\text{Recall} = \frac{\text{true positive}}{\text{true positive} + \text{false negative}} \text{ ----------------- } (5.2)$$

1) Accuracy

Accuracy is that the overall correctness of the model and is calculated because the total of accurate classifications divided by the whole range of categorization.

$$\text{Accuracy} = \frac{\text{true posivive} + \text{true negative}}{\text{true positive} + \text{false positive} + \text{false negative} + \text{true negative}} \quad (5.3)$$

2) F-score

A live that mixes preciseness and recall is that the mean value of preciseness and recall, the standard f-measure or balanced f-score:

$$\text{F-Score} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \text{ ------------------------------ } (5.4)$$

Figure given below shows the bar chart of the performance of both SIFT with SVM (see Figure 12).

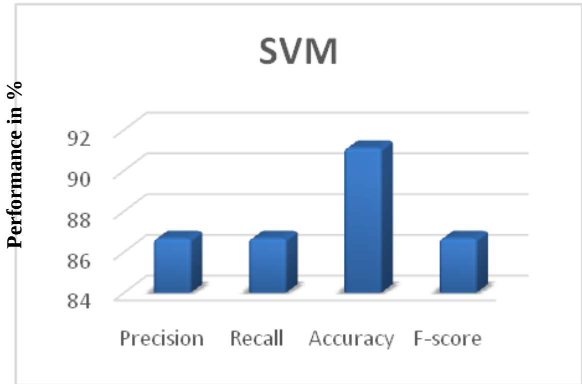

Figure12. Chart represents the performance of real-time outdoor objects with SIFT using SVM

VI. CONCLUSION

The outdoor objects were detected and recognized from the real-time outdoor images. The outdoor objects are detected using Haar-like features and AdaBoost classifier. SIFT features are extracted from the detected objects and classified using Support Vector Machine. The recognition rate for real-time outdoor object using SVM is 91.10%. In future work, a new feature extraction technique will be proposed to recognize the outdoor objects and to improve the performance of the system and the outdoor scene will be recognized.

REFERENCES

[1]. B. Janardhana Rao and O. Venkata Krishna, "The Log Polar Transformation for Rotation Invariant Image Registration of Aerial Images", IJCTA, Vol. 4, Pages: 833-840, 2013.
[2]. S. Sathiya, M. Balasubramanian, V. Vigneshwari, "Traffic Sign Recognition for Advanced Driver Assistance Systems", IJAER, Vol. 9, No. 21, Pages: 5063-5068, 2014.
[3]. Seyyid Ahmed Medjahed, "A Comparative Study of Feature Extraction Methods in Images Classification", IJIGSP, Vol. 7, No. 3, Pages: 16-23, 2015.
[4]. Paul Viola and Michael J. Jones, "Rapid Object Detection using a Boosted Cascade of Simple Features", IEEE, CVPR, 2001.
[5]. Yoav Freund, Robert E. Schapire, "A Short Introduction to Boosting", JJSAI, Vol. 4, No. 5, Pages: 771-780, 1999.
[6]. Arsalan Mousavian, Jana Kosecka and Jyh-Ming Lien, "Semantically Guided Location for Outdoors Scenes", IEEE (ICRA), Pages: 26-30, 2015.

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ISSN (Print) 2319 5940

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 5, Issue 3, March 2016

[7]. Jin Han Lee, Sehyung Lee, Guouan Zhang, Jongwoo Lim, Wan Kyun Chung, and II Hong Suh, “Outdoor Place Recognition in Urban Environments Using Straight Lines”, IEEE(ICRA), Pages: 5550-5557, 2014.
[8]. Ali Borji and Laurent Itti, “Human Vs Computer in Scene and Object Recognition”, CVPR, 2014.
[9]. P. Espinace, T. Kollar, N. Roy, A. Soto, “Indoor Scene Recognition by a Mobile Robot through Adaptive Object Detection”, ELSEVIER (RAS), Vol.61, Pages: 932-947, 2013.
[10]. P. Viola, M. Jones, Robust real-time face detection, IJCV, Vol. 57, No. 2, Pages: 91-110, 2004.
[11]. Lowe, David G. "Distinctive image features from scale-invariant key points. "International journal of computer vision 60.2 (2004): 91-110.

BIOGRAPHIES

R. Arun Kumar received his B.E degree in Electronics and Communication Engineering from A.V.C College of Engineering (AVCCE), Mayiladuthurai in the year 2000. He received his M.E degree in Computer Science and Engineering from Annamalai University in the year 2005. He has been with Annamalai University as an Assistant Professor, since 2002. He is currently perusing Ph.D in Computer Science and Engineering from Annamalai University. He published papers in 10 international journals and conferences. His research interest includes image and video processing and pattern recognition. He is the life term member in ISTE, CSI, UACEE, IAENG and CSTA

Dr. M. Balasubramanian received his B.E degree in Computer Science and Engineering from Government College of Engineering (GCE), Tirune lveli in the year 1996. He received his M.Tech degree in Computer Applications from Indian Institute of Technology, Delhi in the year 2004. He has been with Annamalai University, since 1999. He received Ph.D in Computer Science and Engineering from Annamalai University in the year 2011. He published papers in 25 international journals and conferences. He received Career Award for Young Teachers (CAYT) from All India Council for Technical Education (AICTE), New Delhi. He is the Co-Investigator of an UGC Major Research project since 2012. He has organized workshops in the field of image and speech processing, and Latex. He has delivered special lectures in several topics of his area, in workshops and staff development programme. Currently, five research scholars are pursuing research under his guidance in the area of image and video processing. His research interest includes image and video processing, pattern classification and neural networks. He is the life term member in ISTE, CSI, CSTA, IAENG and UACEE.