www.ijecs.in
International Journal Of Engineering And Computer Science ISSN:2319-7242
Volume 03 Issue 07 July, 2014 Page No. 7044-7053

Target Recognition using Improved SIFT Algorithm

Darshana Vispute[1], Sachin Pable[2], Devidas Dighe[3]
[1]*MCOERC, Nasik, University of Pune.*
[2]*MCOERC, Nasik, University of Pune.*
[3]*MCOERC, Nasik, University of Pune.*

[1]vispute.darshana@gmail.com
[2]sachinp_79@yahoo.co.in
[3]devidasdighe@gmail.com

Abstract:- Robotics is the fastest growing technology in the scientific world. Robotics today is being applied to various industries for different applications. Also it replaces human process and where people are required to do monotonous job repeatedly. At these places robots are found ideal replacements. In this paper we will discuss one such robot localization algorithm called as SIFT algorithm. Scale Invariant Feature Transform (SIFT) is an algorithm in Computer vision to detect local features of image. Identification of target in image processing using SIFT algorithm is proposed in this paper. This SIFT feature descriptor is invariant to uniform scaling, orientation and invariant to illumination changes.

Improvement in SIFT has also been proposed in this paper using the fusion of Discrete Wavelet Transform (DWT), Singular Value Descriptor (SVD) and SIFT algorithm. This combination of algorithm preserves the features from the images. With the help of this proposed technique improved efficiency is obtained in terms of resolution and contrast.

Keywords:- Keypoints, Discrete wavelet transform, Singular Value Decomposition, local features, keypoint localization, etc

I. INTRODUCTION

Due to rapid growth in robotics field, there is needed to develop some algorithm for target identification using image processing. In indoor environment target identification proves very helpful for monotonous kind of jobs. Mostly target identification is used on AGV's which are normally used for industry applications. However for localization in indoor environments GPS may not prove really helpful. Also it may fail to work in non network areas of GPS. Image enhancement is ability that improves the quality of digital image with no knowledge about the source of degradation. This enhancement can be done prior to application of SIFT algorithm so as to improve the resolution of the image. Images are being processed in order to get more enhanced resolution and for this enhancement commonly used technique is Interpolation. But the main disadvantage of interpolation is loss of HF components i.e. edges, caused due to smoothening. To avoid this problem we used transforms such as DWT and SWT as they are redundant and shift invariant. These transforms help to decompose the image into various frequencies sub-band using DWT and resultant image can be obtained by combining the sub-band images using IDWT.

Also for dealing with the illumination problem Singular Value Decomposition (SVD) can be used. SVD has recently emerged as a new tool for processing different types of images. SVD is an attractive algebraic transform for image processing algorithm. Despite the fact that SVD has attractive properties in imaging, exploring the use of its properties in newly image applications is currently at its infancy [1].

The goal of this project is to develop a technique that will identify targets which will emulate human learning and address searching capability by using SIFT transform in real time application.

II. BACKGROUND

Comparison of images to establish degree of similarity has applications in various domains such as content based image retrieval, robot localization, interactive museum guide, image registration etc. image matching becomes a challenging task because of issues such as illumination changes, partial occlusion of objects, differences in image orientation etc. colour histograms, responses to filter banks etc. are global image characteristics which are usually not effective for solving real life image matching problems.

Recently many researchers have turned their attention to extract local features from an image, which are invariant to common image transformations and variations or any image matching scheme. There are two major steps involved in local feature based image matching scheme: First step is to detect keypoints (interest points) from an image in a repeatable way. Repeatability is important at this step as robust matching cannot be performed if the detected locations of keypoints on an object vary from image to image. Second step is to compute descriptors for each detected keypoint.

SVD is the optimal matrix decomposition in a least square sense that it packs the maximum signal energy into as few co-efficients as possible. SVD is generalization of Eigen value decomposition, is used to analyse rectangular matrices. It has been widely used in the field of image compression and watermarking either individually or in combined form with other popular transforms such as Discrete Cosine Transform (DCT), Discrete Wavelet Transform (DWT) and many more. The idea of SVD is to decompose a rectangular matrix into three simple matrices (2 orthogonal and 1 diagonal matrix) [2,3]

The goal is to design a highly distinctive descriptor for each interest point found which would provide meaningful matches for target identification. It also will simultaneously ensure a given interest point will have same descriptor regardless of object position, illumination in environment and image scale. As a result both the steps detection and description rely on invariance of various properties for effective image matching.

III. LITERATURE REVIEW

Robotics is the fastest growing technology in today's world. Whenever a robot is designed it has to be localized to the process also. Depending upon the requirement, robot is adapted to perform those functions repeatedly. Various techniques are used today and most of them are accomplished through the computer. Also changes can easily be made to functionality of robot using a computer. Localization is a critical issue in robotics. Here we are mainly focusing on robot localization application for indoor environment. There is wide variety of localization techniques available. Out of variety of localizations techniques available SIFT proves to be more effective to implement in real time applications.

Image matching techniques using local features for target identification is not new in the image processing field. Sven Siggelkow [3] used feature histograms for content based image retrieval, who achieved relative success with 2D object extraction and image matching. Mikolajczyk and Schmid [5] used differential descriptors for approximation of point neighbourhood for image matching and retrieval. Van Gool [6] introduced the generalized colour moments to describe the shape and intensity of different colour channels in a local region of image. Schaffalitzky and Zisserman [8] used Euclidean distance between orthogonal complex filters to provide a lower bound on the Squared Sum Differences (SSD) between corresponding image patches. Ledwich and Williams [9] used the scale information of the SIFT features to improve location discrimination. Tamimia et.al. [7] proposed in their work that using few keypoints and comparing image content against database can improve speed of SIFT approach. Valgren and Lilienthal [10] investigated how two local feature algorithms SIFT and SURF approach can be used for localization in outdoor environment that undergo seasonal changes for almost a year. Sukthankar [11] introduced an alternate representation for local image descriptor for SIFT algorithm, which is more distinctive and compact leading to significant improvement in matching accuracy for both controlled and real world condition. S. Majumder and T. Das [12] proposed a novel hybrid watermarking scheme and presented with the logo embedded into the DWT based transform domain along with SVD, NVF and CSF. R. Sadek [1] proposed unused SVD characteristics in novel approaches such as adaptive block based compression, perceptual multiple watermarking, image capacity of hiding information , roughness measure etc. Ganesh naga et. Al. [13] proposed the image enhancement technique using DWT and SVD. To increase the resolution use of DWT and SWT is used and to increase the contrast use of SVD and DWT is used. David Lowe [14] proposed Scale Invariant Feature Transform (SIFT), which is robustly resilient to different types of image transforms. Mikolajczyk and Schmid [15] reported an experimental evaluation of several different descriptors where they found that the SIFT descriptors obtain the best matching results.

IV. SELECTION OF LOCAL FEATURES

The following key requirements needed to be considered while selecting a local feature for images used in this project:

(a) *Invariance:* The feature should be supple to the changes in illumination, image noise, uniform scaling rotation, and minor changes in viewing direction.

(b) *Distinctiveness:* The features should provide correct object identification with low probability of mismatch.

(c) *Matching performance:* Whenever input image is given system for identifying target, it should be relatively easy and fast to extract the features and compare the images with the database of local features.

V. ALGORITH DESCRIPTION IN BRIEF

Based on requirements of local features mentioned in previous section and reported robustness in [15], selection of SIFT [14] approach is selected. SIFT is an approach useful for detecting and extracting local feature descriptors that are reasonably invariant to illumination changes, noise in image, rotation, scaling, and small changes in viewpoint. Before performing any multi resolution transformation via SIFT, the image is first converted to greyscale representation. The SIFT features are local features which are based on the appearance of the object at specific interest points and are invariant to image scale and rotation. SIFT features are robust to changes in illumination, noise and minor changes in viewpoint. They are also relatively easy to match against a database of local features but however the high dimensionality can be issue, and generally probabilistic algorithms such as k-d trees with best in first search are used.

A complete detail explanation of algorithm is found in [14]. An brief description of algorithm is presented in this paper. The algorithm has basic four major stages as mentioned below:

A. Scale space extrema detection: The SIFT feature algorithm is based upon finding keypoints within the scale space of an image which can be extracted reliably. We want to find points that give us information about the objects in the image. The information about the objects is in the object's edges. So represent the image in a way that gives these edges as these representations extrema points. These keypoints correspond to local extrema og difference-of-Gaussian (DoG) filters at different scales. Find the points, whose surrounding patches (with some scale) are distinctive. An approximation to the scale-normalized Laplacian of Gaussian

$$L(x,y,\sigma)=G(x,y,\sigma)*I(x,y)$$

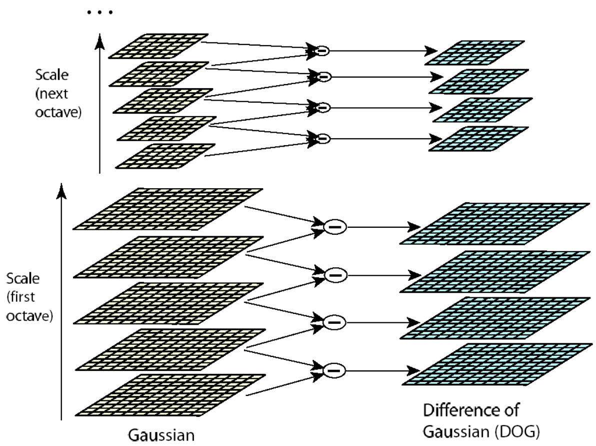
Where L(x,y,σ) is the scale space of an image, built by convolving the image I(x,y) with the Gaussian kernel G(x,y,σ)

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

Each Keypoint is represented as (x,y,σ). The DoG image is represented as D(x,y,σ) and can be computed from the difference of two nearby scaled images separated by a multiplicative factor k:

$$\begin{aligned}D(x,y,\sigma)&=\left(G(x,y,k\sigma)-G(x,y,\sigma)\right)*I(x,y)\\&=L(x,y,k\sigma)-L(x,y,\sigma)\end{aligned}$$

The convolved images are grouped by octave. An octave corresponds to doubling the value of σ, and the value of k is selected so that the fixed value of blurres images are generated per octave. This also ensures the same number of DoG images are obtained per octave. Keypoints are identified as local maxima or minima of the DoG images across different scales. Each pixel in a DoG image is compared to its 8 neighbours at the same scale shown in fig. 1, and the 9 corresponding neighbours at neighbouring scales. If the pixel is a local maximum or minimum, it is selected as a candidate keypoint.



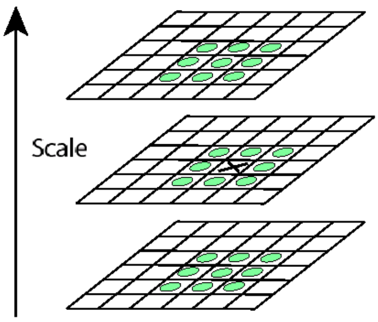


Figure 1. Difference of Gaussian
Figure 2. Extracting keypoints

X is selected if it is larger or smaller than all 26 neighbours, which is shown in fig. 2. If the pixel is lower/higher than all its neighbours, then it is labelled as candidate point. Each of these is exactly localized by Taylor expansion series.

B. Keypoint Localization: There are still a lot of points; some of them are not good enough. The locations of keypoints may be not accurate. So there is need to eliminate edge points. Inaccurate localization is mainly caused due to scaling and sampling. Low contrast images are generally sensitive to noise and have strong edge responses. The Problem caused due to inaccurate localization is as shown in fig. 3.

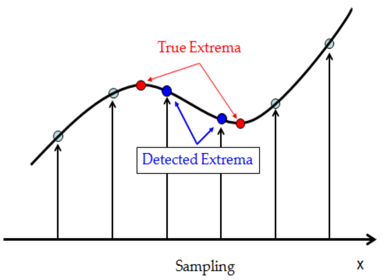


Figure 3. Mismatch between detection of extrema

The solution is to use the Taylor expansion series as below:

$$D(\vec{x}) = D + \frac{\partial D^T}{\partial \vec{x}}\vec{x} + \frac{1}{2}\vec{x}^T \frac{\partial^2 D^T}{\partial \vec{x}^2}\vec{x}$$

The keypoints are then filtered by discarding points of low contrast and points that belong to edges. Equation 5 shows how we can minimize to find accurate extrema.

$$\hat{x} = -\frac{\partial^2 D^{-1}}{\partial \vec{x}^2}\frac{\partial D}{\partial \vec{x}}$$

If offset from sampling point is larger than 0.5 keypoint should be in a different sampling point. Here first 3D quadratic function is fitted to the local sample points to determine the location of the maximum. The function value at the extremum is used for rejecting unstable extrema with low contrast. The DoG operator has a strong response along edges present in an image, which give rise to unstable key points. A poorly defined peak in the DoG function will have a large principal curvature across the edge but a small principal curvature in the perpendicular direction. The principal curvatures can be computed from a 2x2 Hessian matrix H, computed at the location and scale of the keypoint. H is given by:

$$H = \begin{bmatrix} D_{xx} & D_{xy} \\ D_{xy} & D_{yy} \end{bmatrix}$$

The eigenvalues of H are proportional to the principal curvatures of D. However eigenvalues are not explicitly computed; instead trace and determinants of H are used to reject those keypoints for which the ratio between principal curvatures is greater than a threshold.

C. Orientation assignment: Here we assign an orientation to each keypoint, to make descriptor invariant to rotation. The keypoint descriptor can be represented relative to this orientation and therefore achieve invariance to image rotation. Computing magnitude and orientation on the Gaussian smoothed images is also done in this step.

This keypoint orientation is calculated from an orientation histogram of local gradients from the closest smoothed image L (x,y,σ). For each image sample L(x, y) at this scale, the gradient magnitude m(x,y) and orientation θ(x, y) is computed using pixel differences:

$$m(x,y) = \sqrt{(L(x+1,y)-L(x-1,y))^2 + (L(x,y+1)-L(x,y-1))^2}$$

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

The orientation histogram has 36 bins covering the 360 degrees of major orientation bins. Each point is added to the histogram weighted by the gradient magnitude m(x, y) and by a circular Gaussian with σ that is 1.5 times the scale of the keypoint.

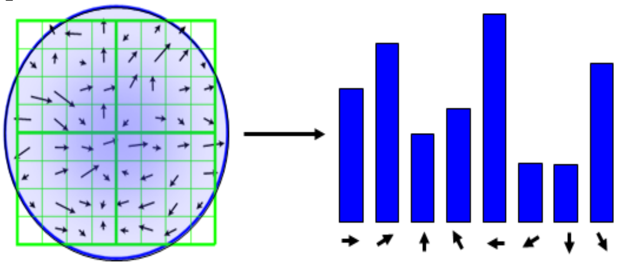


Figure 4. Histogram of element vector

A histogram is formed by quantizing the orientations into 36 bins, is shown in fig. 4. Peaks in the histogram correspond to the orientations of the patch. For the same scale and location, there could be multiple keypoints with different orientations. Any histogram peak within 80% of highest peak is assigned to keypoint. The dominant peaks in the histogram are interpolated with their neighbors for a more correct orientation assignment.

D. Keypoint descriptor: The local gradient of data from the closest smoothed image L(x,y,σ). Is also used to create the keypoint descriptor. This gradient image is first rotated with θmax to align it with assigned orientation of keypoint with horizontal direction in order to provide rotation invariance shown in fig. 5. After this rotation, the region around the keypoint is subdivided into 4*4 square sub regions. From each sub region, an 8 bin sub orientation histogram (SOH) is built as shown in fig. 5.

In order to avoid boundary effects, trilinear interpolation is used to distribute the value of each gradient sample into adjacent histogram bins. Typical keypoint descriptors use 16 orientation histograms aligned in a 4*4 grid. Each histogram orientation histogram has 8 orientation bins each created over a support window of 4*4 pixels. Finally, the 16 resulting SOHs are transformed into 128-D vector. The vector is normalized to unit length to achieve invariance against illumination changes. This vector is called as SIFT descriptor and is used for similarity measuring between two SIFT features.

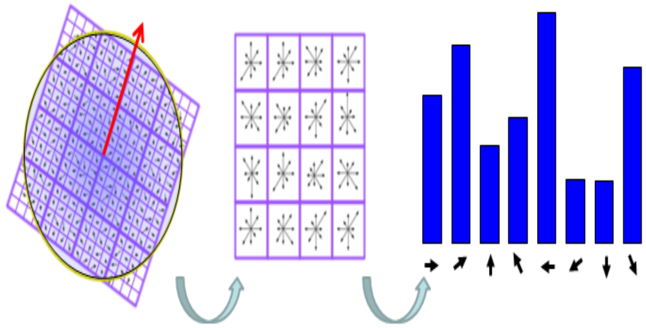


Figure 5. 128(4*4*8) element vector

VI. MATCHING OF KEYPOINTS

Implementation of target identification can be done on real time basis. Using camera with the system and setting it on continuous video mode is to be performed. Then from that continuous video frames are needed to be grabbed at a specific interval of time. This grabbed frame each time will act as a input test image for matching purpose.

Whenever the input test image is given each of its keypoint is compared with keypoints of image present in the database. At first the Euclidean distance is calculated between each invariant feature descriptor of the test image each invariant feature descriptor of the database image. However the two keypoints with the minimum Euclidean distance (closest neighbours) may not match necessarily because many features from an image may not have correct match in the database of images either because of background clutter or may be the feature was not detected at all. Instead the ratio between the closest neighbours and distance between the second closest neighbors is computed. If the ratio value is greater than 0.6, then the match is rejected. Each time the number of matched keypoints is shown, whenever the reach is maximum we can terminate the execution of the algorithm and system is set for robotic localization and navigation purpose. Navigation is not the scope of this project.

VII. IMPROVED ALGORITHM

Resolution and contrast are two important attributes of an image. For the purpose of enhancement of image in terms of resolution and contrast the proposed technique can be used for the purpose of target identification. To increase the resolution use of DWT and SWT is done. With the help of these transforms the input image is decomposed into four sub bands out of which one is LF and others are HF bands. The HF components from the image are interpolated and then use of IDWT is used to combine interpolated HF and LF components. To increase the contrast use of SVD and DWT is done in the algorithm. The main disadvantage of using interpolation is the loss of HF components i.e. edges, which is due to the smoothening caused by performing interpolation. Preserving of edges is necessary so DWT is used to overcome this problem. Image enhancement is done in two stages resolution enhancement and contrast enhancement [13].

A. *Resolution Enhancement*: The proposed technique is based on interpolation of HF sub band images obtained by DWT and the input image. Here main role of DWT is to preserve HF components. After decomposition of images interpolation is done by bi-cubic interpolation method with enlargement factor 2. Down sampling causes information loss in respective sub bands so use of SWT is done to minimize the errors. It is seen that interpolated HFD bands and SWT HF bands have same size and so they can be added together. Also instead of using LL band, input image is used as it contains more information and increases quality of super resolved image. This is due to the fact that, interpolation of HF components in HF sub bands and using the corrections obtained by HF components of SWT of the input image will preserve more HF components then the ordinary interpolation.

B. Contrast Enhancement: Output of resolution enhancement is given as input to this block. Important tools used here are SVD and DWT. DWT divides the image into different sub bands. After application of DWT then calculate hanger (u), aligner (V) and singular value matrix (SVM) for LL sub bands. Find maximum values in both SVM's and take their ratio (ξ). Calculate SVM and estimate the new LL sub band value

$$LLA(new) = ULLA\ \ \Sigma LLA\ VLLA \qquad (8)$$

The estimated LL sub band and the HF components of actual input image is used to reproduce the contrast enhanced image. As no HF components are disturbed only manipulation of illumination information is done. So there is no harm to edge components.

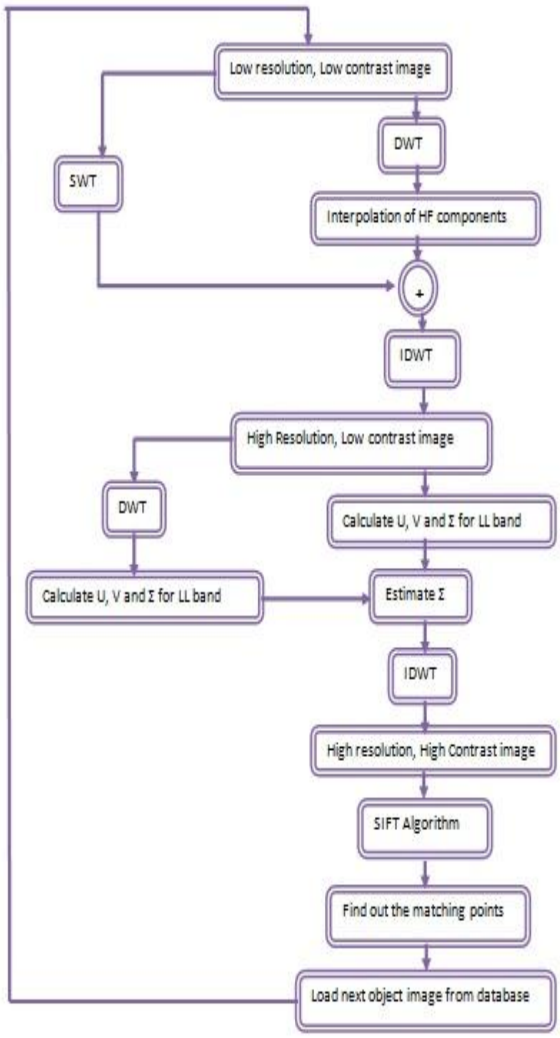


Figure 6. Process flow of proposed technique

VIII. IMPLEMENTATION

The approach described above has been implemented using MATLAB. This implementation can be classified into two aspects: matching and inference. During matching phase locally invariant features (keypoints, orientation, scales and descriptors) from input test images are retrieved using SIFT algorithm and stored in a file. During inference the main objective is to recognize a input test image. A set of local invariant features are retrieved for the test image during inference phase and compared using the metric explained in section V.

An important aspect of SIFT is that it generates large number of features for wide range of scales and locations. The number of features generated mainly depends on image size and content, as well as algorithm parameters. If the obtained test images are of higher resolution then down sampling is necessary to reduce the number of keypoints.

Figure 7. Stepwise implementation

Above fig 7 shows the steps for the execution of the target identification using DWT and SVD prior to SIFT. As a result input image is low resolution and with low contrast, then after processing input image given to SIFT algorithm is with high resolution and high contrast in order to increase the efficiency.

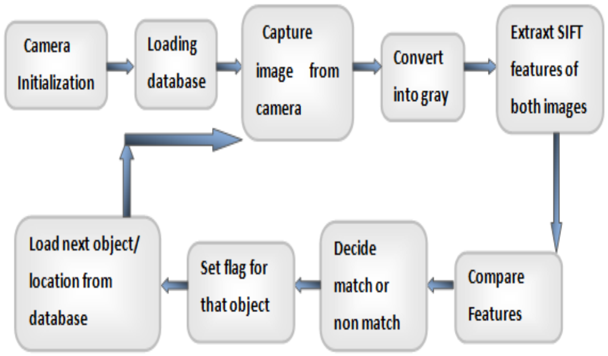


Figure 8. Block diagram of SIFT Algorithm

Above fig. 8 depicts about the working of the target identification system. Camera initialization is done with winvideo adapter in manual trigger mode. Loading of object from database is done following with capturing of image from camera. SIFT features are only extracted when the image are converted to gray. Comparison of these features is performed and matching keypoints are decided. If the value obtained is above threshold then target is said to be identified. If not final destination then load next images from database and again repeat the steps.

Factors to be considered while implementing a system in real time

Computational expense: It should be computationally inexpensive so modern PC has enough power to run it.

Moving background rejection: Misclassification can easily occur if the area of moving background is large compared to the object of interest.

Tracking through occlusion: Many algorithms still fail to track the image if it is occluded for longer period of time.

Adapting to illumination variation: Real world applications will inevitably have variation in scene illumination, so that a target identification algorithm needs to overcome illumination changes.

Analysing object motion: This could be difficult for non rigid objects such as humans if objects view is not in the right perspective for the algorithm.

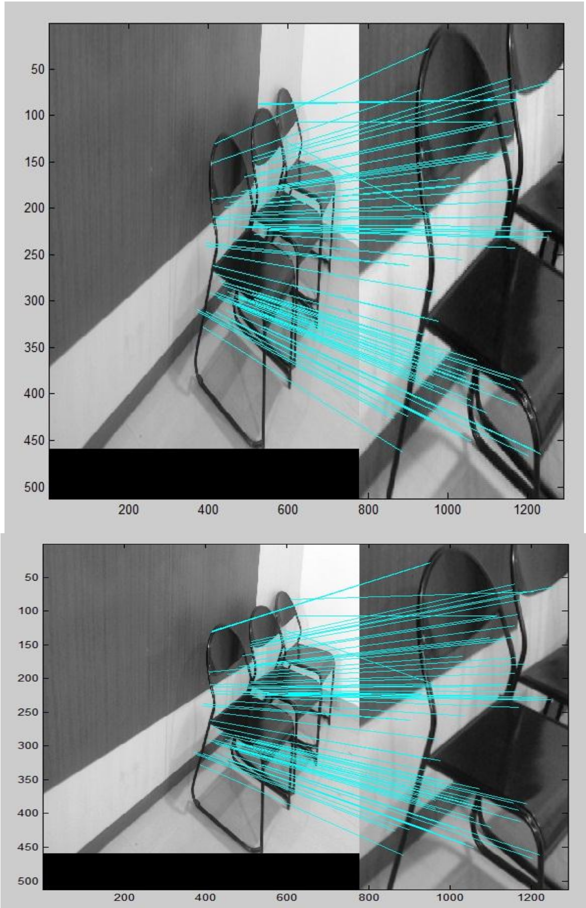
Adapting to camera motion: Detecting moving entities from video streams still remains a challenge in this research field.

VIII. SIMULATION RESULTS

The SIFT algorithm was implemented first on images from the database only. Scene image and object image are the two images that are to be compared. Object image consist of main image which is stored in database and match of this object image is to be traced in scene image. Initially for simulation scene image is also stored in the database. For real time implementation scene image is that image which is captured by camera. After certain interval of time frame from an video is grabbed, and thus that frame becomes the scene image. Table 1 below depicts the comparison of matching points obtained for best case and worst case by using SIFT algorithm only. As a result there is need to develop some technique which would enhance the performance of SIFT algorithm. Various techniques can be used to improve the performance of SIFT which are explored in next Section. According to application the suitable technique can be chosen.

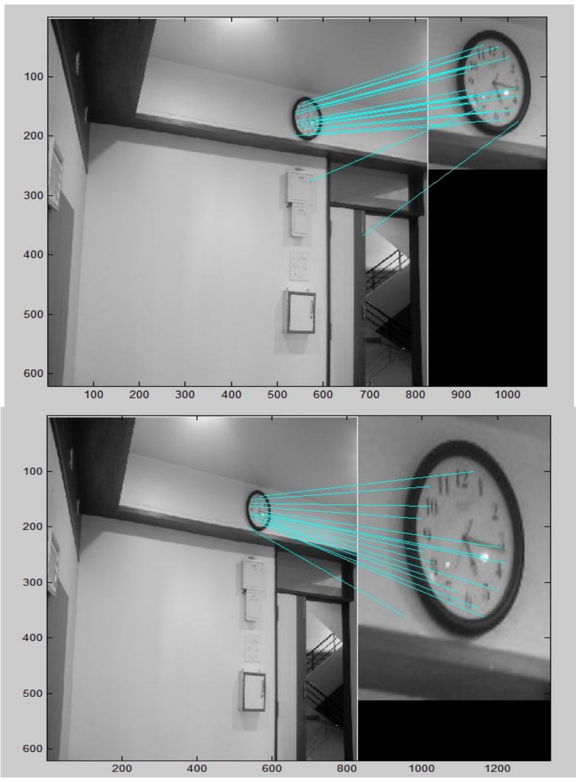
Table 1. Comparison of matching points

Variation parameters	Best case	Worst case
Illumination	Intensity : 1 Matches : 121	Intensity : 5 Matches : 40
Scale	Size : 0.8 Matches : 305	Size : 0.1 Matches : 153
Rotation	Angle : 0 degrees Matches : 305	Angle : 30 degrees Matches : 153



(a)

Fig 9. Simulation results chair image



(a)

(b)

Fig 10. Simulation results clock image

Fig. 9 (a) shows the simulation results obtained for chair image using SIFT algorithm and (b) shows the results obtained for chair image using proposed algorithm. Fig. 10 (a) shows the results obtained by using SIFT algorithm for clock image and (b) shows results by proposed technique for clock image. From images we can observe that it improves matching points as compared to SIFT algorithm. Table 2 depicts the comparison parameters with respect to matching points and execution time.

Table 2 Comparison of simulation results with SIFT and Proposed Algorithm

Fig. No.		Matching Points	Execution time
Fig 9	(a)SIFT	68	2.7 secs
	(b) Proposed technique	75	3.2 secs
Fig 10	(a)SIFT	16	3.5 secs
	(b) Proposed technique	16	4.1 secs

(b)

IX. FUTURESCOPE

In order to improve the performance of the SIFT algorithm in various aspects, further research can be done. Some improvement parameters are mentioned below:

A. Super resolution of input images: Super-Resolution (SR) is a technique by which a number of Low Resolution images are combined into a single High Resolution image. This has a greater resolving power. Super Resolution is not only useful to enhance the resolving power of an image; also it can reduce the aliasing noticeably. At an initial level it may take a longer time for execution for higher resolution images but improvements can be done to increase the execution speed.

B. Global features: An image may have many keypoints that are similar to each other locally. These multiple similar areas may produce indistinctness while matching of local descriptors. The local invariant features of SIFT can be improved by computing global features of image.

C. Difference of mean: As mentioned in [8], instead of using the DoG of images for finding out signal space extrema, we can also use Difference of Mean (DoM) images to approximate DoG. For finding out

DoM of images first need is to compute an integral image. An integral image can be computed from an input image I as mentioned below:

$$J(x,y) = \sum_{x'=0}^{x}{}' \sum_{y'=0}^{y} I(x,y) \quad (8)$$

The mean of rectangular region of an integral image can be computed very efficiently and doesn't depend on size of the region.

X. CONCLUSION

This project proved to be a compelling exploration of applications of image processing techniques. SIFT is the state-of-the-art algorithm for extraction of locally invariant features and this project makes us understand about the multi resolution image analysis and its application in target identification. From simulation results it can be observed that using proposed method improves matching points but it also increases the time taken for execution. This increase in time is basically due to increase in resolution of images. Thus this algorithm is successful in terms of matching points and proves that it improves efficiency as compared to conventional SIFT method. The negligible disadvantage of this proposed algorithm is that execution time required is more than the conventional SIFT method. Efforts for this project resulted in robust target identification implementation which performs really well in real time applications.

ACKNOWLEDGMENT

Authors are thankful to the teaching staff for their support and express deep sense of gratitude towards the guide who always encouraged working on this algorithm as a dissertation.

REFERENCES

[1] Rowayda A Sadek, "SVD based image processing applications: State of the ART, Contributions and Research Challenges," IJACSA, vol. 3, no. 7,pp 26-34, 2012

[2] Liu R., T. Tan, "A SVD based watermarking scheme for protecting rightful ownership," IEEE Tranasac. On multimedia, vol. 4, pp 121- 128, 2002.

[3] S. Majumder et. Al., "SVD and error control coding based digital Image watermarking," IEEE CS proceedings of Act 2009, pp 60-63.

[4] Sven Siggelkow."Feature Histograms for Content-Based Image Retrieval".PhD Thesis, Albert-Ludwigs-University Frieiburg, December 2002.David G. Lowe.Distinctive Image Features from Scale-Invariant Keypoints. International Journal of Computer Vision, 60, 2 (2004), pp. 91-110.

[5] Mikolajczyk, K., Schmid, "An Affine Invariant Interest Point Detector". In: ECCV, (2002) pp. 128-142.

[6] Van Gool, T. Moons, and D. Ungureanu."Affine photometric invariants for planar intensity patterns," In ECCV, pp. 642-651, 1996.

[7] H. Tamimia, H. Andreasson, Andr´e Treptowa, and T. Duckettc, A. Zella," Localization of Mobile Robots with Omnidirectional Vision using Particle Filter and Iterative SIFT," 2006 Elsevier, Robotics and Autonomous Systems vol. 54, pp. 758–765,2006.

[8]] Schaffalitzky, F., Zisserman, "A.: Multi-view Matching for Unordered Image Sets", In: ECCV, (2002) pp. 414-431 .

[9] L. Ledwich, S. Williams," Reduced SIFT Features For Image Retrieval and Indoor Localization," ARC Centre of Excellence for Autonomous Systems School of Aerospace Mechanical and Mechatronic Engineering University of Sydney, NSW, 2006, Australia.

[10] C. Valgren, J. Lilienthal," SIFT, SURF & Seasons: Appearance-based Long-term Localization in Outdoor Environments," AASS Research Centre, Dept. of Computer Science, Orebro University, SE-70182, Orebro, Sweden

[11] Y. Ke1, R. Sukthankar, "PCA-SIFT: A More Distinctive Representation for Local Image Descriptors", School of Computer Science, Carnegie Mellon University; 2 Intel Research Pittsburgh.

[12] M. Moonen, P. Dooren, J. Vandewalle, "Singular value decomposition updating algorithm for subspace tracking." SIAM Journal on Matrix Analysis and Applications, 1992.

[13] Ganesh N. Et. Al., "Image enhancement using Wavelet transforms and SVD," IJEST, vol.4 no. 3, pp 1080-1087, 2012.

[14] D. G. Lowe, "Distinctive Image Features from Scale-Invariant Keypoints," Computer Science Department University of British Columbia Vancouver, B.C., Canada, lowe@cs.ubc.ca, January 5, 2004.

[15] Mikolajczyk, K., Schmid, C.: "Indexing Based on Scale Invariant Interest Points". In: ICCV, (2001) pp. 525–531

[16] S. Se, D. Lowe, J.Little,"Global Localization using Distinctive Visual Features," Proceeding of 2002 IEEE, intl. conference on robots and system, Switzerland.

[17] T. Konda, Y. Nakamura, "A new algorithm for singular value decomposition and its parallelization, parallel Computing, 2009.
[18] H. C. Andrews and C. L. Patterson, 'Singular value decomposition and Digital image processing," IEEE Transac. On Acoustics, Speech and Signal Processing, vol. ASSP-24, pp 26-53, 1976.
[19] Julie L. Kamm, "SVD based methods for signal and image restoration," PhD thesis, 1998.
[20] David G. Lowe. "Object recognition from local scale-invariant features". International Conference on Computer Vision, Corfu, Greece (September 1999), pp. 1150-1157.
[21] Michael Grabner, Helmut Grabner, and Horst Bischof,"Fast approximated SIFT". Proc. ACCV 2006, Hyderabad, India.
[22] Hasan Demirel and Gholamreza Anbarjafari, "Image Resolution Enhancement by Using Discrete and Stationary Wavelet Decomposition" IEEE transactions on IMAGE PROCESSING, VOL. 20, NO. 5
[23] H. Demirel and G. Anbarjafari, "Satellite image resolution enhancement using complex wavelet transform," IEEE Geosciences and Remote Sensing Letter, vol. 7, no. 1, pp. 123–126, Jan. 2010.
[24] Kirk Baker," Singular Value Decomposition Tutorial". March 29, 2005
[25] T. K. Kim, J. K. Paik, and B. S. Kang, ''Contrast enhancement system using spatially adaptive histogram equalization with temporal filtering,'' IEEE Trans. Consum. Electron. vol. 44, no. 1, pp. 82--87, Feb. 1998.
[26]H. Demirel, G. Anbarjafari, and M. N. S. Jahromi, ''Image equalization based on singular value decomposition,'' in Proc. 23rd IEEE Int. Symp.Comput. Inf. Sci., Istanbul, Turkey, Oct. 2008, pp. 1--5.