International Journal of Engineering Research and Applications (IJERA) ISSN: 2248-9622
National Conference on Advances in Engineering and Technology
(AET- 29th March 2014)

RESEARCH ARTICLE OPEN ACCESS

Comparison of Various Algorithms used for Object Detection

Malveen Kaur*, Hempriya**
*(Department of Electronics and Communication Engineering, Rayat and Bahra Institute of Engg. & Biotechnology, Sahauran, Punjab, India
Email: montybhinder@gmail.com)
**(Department of Electronics and Communication Engineering, Rayat and Bahra Institute of Engg. & Biotechnology, Sahauran, Punjab, India
Email: hempriya.bassi@gmail.com)

ABSTRACT
Recently, demand for object recognition is rising with the increase of digital images. In this paper, a performance comparison of some object recognition techniques has been made. In a dataset, images usually contain wide background areas other than the object area which is focused in the recognition. This unnecessary areas should be ignored to increase the efficiency and accuracy of object detection. In this paper, we also discuses some applications of object detection in real time world and concentrate on crack detection as an application of object detection. Crack detection of objects is used in various manufacturing companies like utensil companies and spare part manufacturing companies.
***Keywords* -** Edge Detection, Image Processing, Image Classification, Object Detection

I. INTRODUCTION

Object recognition is a fundamental and challenging problem and is a major focus of research in computer vision, machine learning and robotics. The task is difficult partly because images are in high-dimensional space and can change with viewpoint. The core of building object recognition systems is to extract meaningful representations (features) from high dimensional observations such as images, videos, and 3D point clouds. Object detection is used to distinguish the objects by considering their shapes, size, and some other useful features. As in [3] Keypoints are extracted from the entire image without discrimination, keypoints from the object class are useful rather than from image noise and background clutter. Most frequent and meaningful keypoints are included in the feature vector, while ignoring random and meaningless keypoints. Most of systems share a general structure of four building blocks: Image acquisition, preprocessing of the images, feature extraction, and classification. To improve the classification results in various situations, many approaches have been studied including decision theory, feature selection, optimization and learning etc. Kernel descriptors [1] provide a unified way to generate rich visual feature sets by turning pixel attributes into patch-level features, and yield impressive results on many object recognition tasks. They can also be naturally extended to extract features over depth images. Different techniques are used to detect different objects which are used in our daily routine as shown in Fig 1.

Fig 1: Different objects used for detection in real world

The core of a robust recognition system is to extract meaningful representations (features) from high-dimensional observations such as images, videos, 3D point clouds and audio [10]. The extracted features must be highly distinctive, have a low probability of mismatch, should be tolerant to image noise, changes in illumination, uniform scaling, rotation, and minor changes in viewing direction. Most of the approaches to object recognition using descriptors can be documented in four steps: Keypoint matching, nearest neighbor indexing, clustering, and solutions for affine parameters [3].

II. APPLICATIONS OF OBJECT DETECTION

There are various applications of object detection used in real world. Some of them are given as follows:

(a) Object Detection is also used to detect cracks in manufacturing companies.

(b) Object detection is also used in vehicle number plate detection.

(c) Face animation effects for the entertainment industry.

(d) Video surveillance systems with automatic face identification.

(e) Object detection has also application in the security purpose.

(f) Used in digital camera image to detect the different images.

(g) Object detection is used in medical line as an application to skin cancer screening.

III. TECHNIQUES USED FOR OBJECT DETECTION AND CRACK DETECTION

Some of the techniques used to detect objects in real world are Object Recognition with Hierarchical Kernel Descriptors, Depth Kernel Descriptors for Object Recognition, Real object recognition using moment invariants [11], Mining spatial related features for object recognition , SVM used in Segmentation as Selective Search for Object Recognition [6], Real-Time Human Pose Recognition from Depth Image, Fast Concurrent Object Localization and Recognition, Seam Carving and Saliency Map [7], technique based on mathematical Morphology and Correlation Coefficient [8], Using Stereo [9], Efficiently Combining Contour and Texture Cues for Object Recognition. Dataset consisting of segmented RGB and depth images are used. Each techniques have its own advantages and disadvantages and also having different applications. Brief explanations of some papers using various techniques are given below:

3.1 Probabilistic Categorization of Kitchen Objects:

In [12], authors presented a system that can extract features from different sensor modalities for solving the problem of classifying different objects present in kitchen environments as shown in Fig. 2 and Fig. 3. Authors used statistical relational learning methods (Markov Logic Networks and Bayesian Logic Networks) to capture complex interactions between the different feature spaces. To show the effectiveness of approach, proposed system is analyzed and validated for the problem of recognizing objects in table settings scenarios. The classification results (Table 1), which indicate an overall classification rate of about 54%, yet the accuracy on properly segmented objects is almost 70%. The time taken for a run of the feature estimation and the classifier on a single scene was a few seconds.

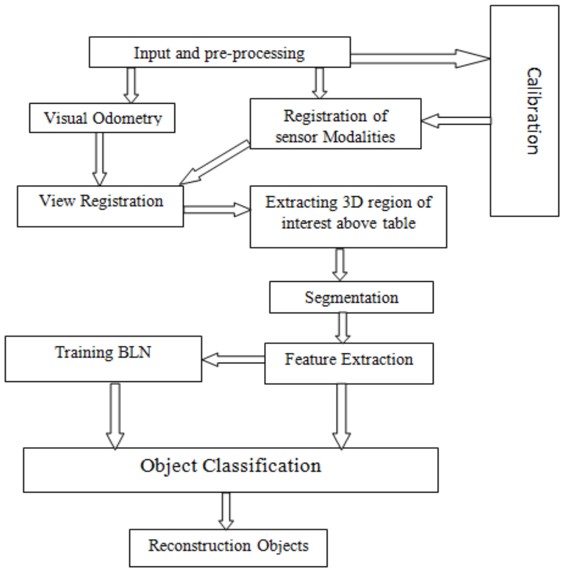

Fig 2: Probabilistic Categorization of Kitchen Objects

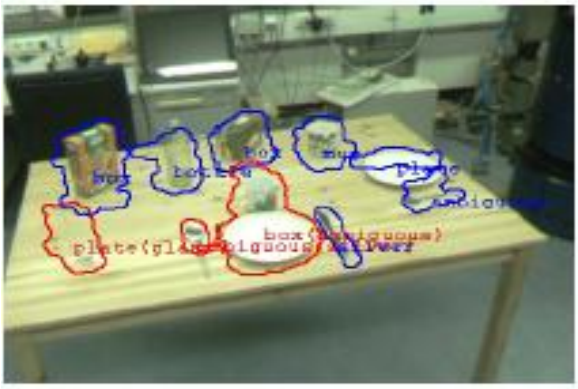

Fig 3: Correctly classified clusters are marked with blue, while incorrectly classified ones with red, and the ground truth is shown in parenthesis

Table 1: Table for Categorization Result

Class	Correct	Number	Ratio
1 - box	23	27	0.85
2 - plate	52	67	0.78
3 - glass	7	31	0.23
4 - mug	39	40	0.98
5 - bottle	4	5	0.80
6 - silver	21	43	0.57
7 - ambiguous	17	87	0.20
overall (1-7)	163	300	0.54
objects (1-6)	146	213	0.69

3.2 Depth Kernel Descriptors for Object Recognition:

Motivated by local descriptors on images, in particular kernel descriptors [2], authors developed a set of kernel features on depth images that model size, 3D shape, and depth edges in a single framework as shown if Fig. 4. Through extensive experiments on object recognition, author demonstrated that (1) local features capture different aspects of cues from a depth frame/view that complement one another; (2) kernel features significantly outperform traditional 3D features (e.g. Spin images); and (3) significantly improve the capabilities of depth and RGB-D (color + depth) recognition, achieving 10−15% improvement in accuracy over the state of the art. Authors proposed a range of local features over a depth image and showed that for object recognition they are superior to pose-invariant features like Spin Images.

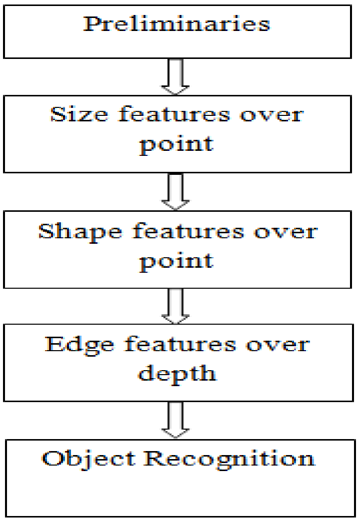

Fig 4: Flowchart for object detection using Depth Kernel Descriptors

Table 2: Accuracies of depth kernel descriptors on the RGB-D object dataset (in percentage)

Features	Instance	Category
Size KDES	32.0	60.0±3.3
KPCA	29.5	50.2±2.9
Spin KDES	28.8	64.4±3.1
Gradient KDES	39.8	69.0±2.3
LBP KDES	36.1	66.3±1.3
Combination	**54.3**	**78.8±2.7**

Table 2 shows the accuracy of depth kernel descriptors, where Size KDES means size kernel descriptors; KPCA means kernel PCA based shape features; Spin KDES means spin kernel descriptors; gradient KDES means gradient kernel descriptors; LBP KDES means local binary pattern kernel descriptors. ± means standard deviation.

3.3 Mining Spatial Related Features:

High probability is that keypoints are related and reliable enough to give more weight when forming the feature vector. Their approach is important because only the most frequent and meaningful keypoints are included in the feature vector, while ignoring random and meaningless keypoints as shown in Fig. 5. Moreover, keypoints belonging to a spatial relationship will be given more weight than independent keypoints [1].

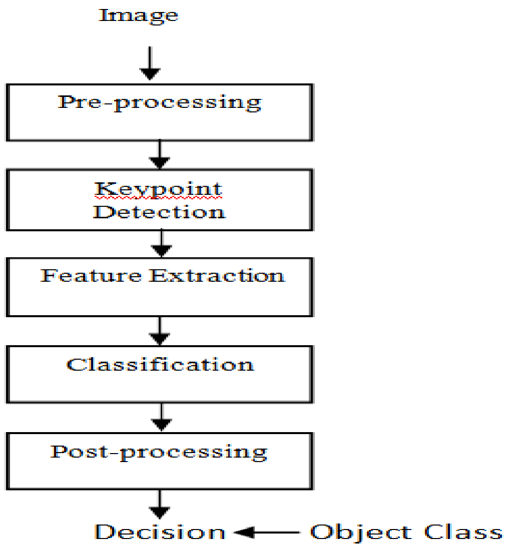

Fig 5: Flowchart for object detection by constructing feature vectors.

The approach [3] is appealing because we believe that a clear pattern can easily be learnt by using machine learning techniques (Fig. 6) if we provide a set of small but extremely meaningful attributes (keypoints features).

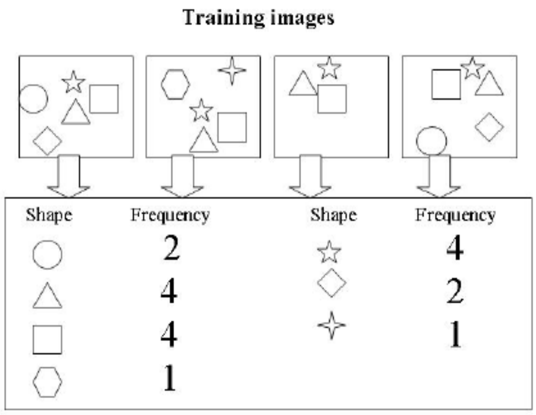

Fig 6: Extracting most frequent features

3.4 Object Recognition based on Mathematical Morphology and Correlation Coefficient:

A technique based on slicing the image to equally sub-areas, and then appling the density slicing to the colour histogram of these areas combined with the color pair technique and then shape recognition method is proposed [4] as a higher level phase in proposed system. This new approach may be categorized under the region-based methods for shape-based retrieval as shown in Fig. 7 and Fig. 8. The approach is capable of solving the most prominent drawback of using region-based methods that is the problems related to unrelated intensity edges to the boundary of the objects within the image as shown in Table 3. Use of Laplacian of Gaussian removes the unwanted intensity edges formulated through noise [4].

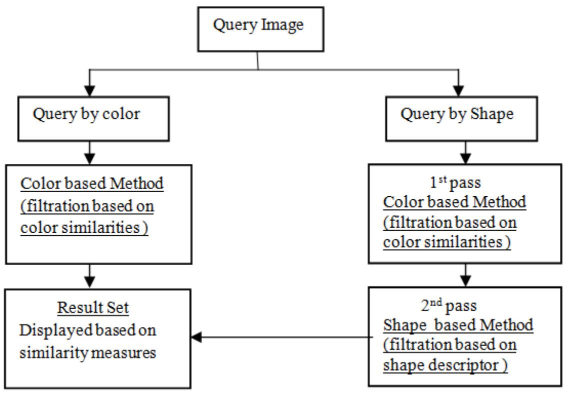

Fig 7: System Flow diagram for object recognition using shape feature extraction.

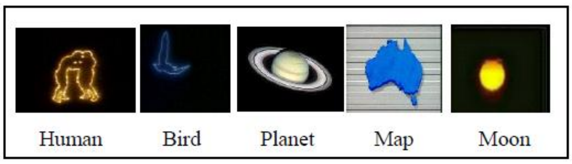

Fig.8: Sample images

Table 3: Execution time in seconds.

	Execution time in seconds		
	$r \geq 0.50$	$r \geq 0.80$	$R \geq 0.10$
Human	4.70	2.73	6.03
Bird	6.86	2.13	8.05
Planet	6.48	4.23	9.18
Map	3.42	1.89	4.08
Moon	5.05	3.57	7.41
Average	5.302	2.91	6.95

3.5 Automation of pavement surface crack detection using the continuous wavelet transform:

It presents a new approach in automation for crack detection on pavement surface images. The method is based on the continuous wavelet transform as shown in Fig. 9. In the first step, a separable 2D continuous wavelet transform for several scales is performed. Complex coefficient maps are built. The angle and modulus information are used to keep significant coefficients. Then, wavelet coefficients maximal values are searched and their propagation through scales is analyzed. Finally, a post-processing gives a binary image which indicates the presence or not of cracks on the pavement surface image. Consequently, author have chosen to work with images whose spatial resolution is between 1 and 2 mm per pixel [5].

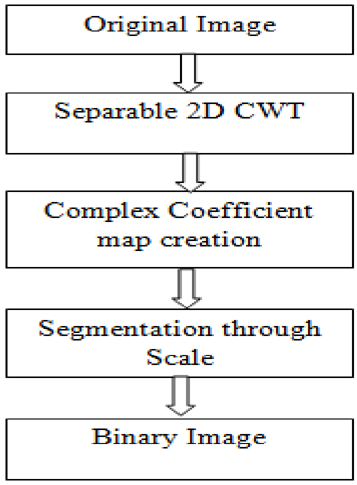

Fig 9: Flowchart of crack detection using continuous wavelet transforms.

IV. Conclusion:

With the help of different techniques, we can detect shape of different objects and cracks in real world. In this paper, we gave a comparison among different techniques used for object detection. Crack detections play important role to find the defects during manufacturing like in pipelines, in utensils and spare parts of machines and we can also able to find the cracks in roads, buildings and surface of earth during earthquakes . Object Detection is used to find the shape of object and to find th categiory of object. Depth Kernel considers the model size, 3D shape, and depth edges in a single framework of depth image. Construting feature vectors is used in mining spatial related features, bag-of-features technique is used in seam carving and saliency map, stereo method is also used for object recognition, shape feature extraction is used in object recognition based on mathematical morphology and correlation coefficient and SVM technique is used in segmentation as selective search for object recognition. We are trying to make a technique which will improve the efficiency and accuracy of object Recognition and also detect the defective piece by detection of cracks or some damage in their shape.

REFERENCES

[1] Liefeng Bo ,Kevin Lai, Xiaofeng Ren, Dieter Fox, "Object Recognition with Hierarchical Kernel Descriptors", *IEEE International Conference on Computer Vision and Pattern Recognition (CVPR), 2011, 1729-1736.*

[2] L. Bo, X. Ren, and D. Fox. "Kernel Descriptors for Visual Recognition", *In NIPS, 2010, 1-9.*

[3] Edmond Zhang, "Mining Spatially Related Features for Object Recognition", *NZCSRSC, 2008, 271-273.*

[4] Muharrem Mercimek, Kayhan Gulez and Tarik Veli Mumcu, "Real object recognition using moment invariants", *SADHANA, 30 (6), 2005, 765-775.*

[5] Peggy Subirats, Jean Dumoulin, Vincent, Legeay and Dominique Barba, "Automation of pavement surface crack detection using the continuous wavelet transform", *IEEE 1-4244-0481-9/06, 2006.*

[6] Koen E. A. van de Sande, Jasper R. R. Uijlingsy-University of Amsterdam , Theo Gevers, Arnold, W. M. Smeulders, "Segmentation as Selective Search for Object Recognition", *International Journal of Computer Vision, Volume 104 (2), 2013, 154-171.*

[7] Motoaki Sato and Jiro Katto, "Performance important of generic object recognition by using seam carving and saliency map", 2011.

[8] Jehad Alnihoud, "An efficient region-based approach for object Recognition and retrieval based on mathematical Morphology and correlation coefficient", *The International Journal of Information Technology, 5 (2), 2008.*

[9] Scott Helmer and David Lowe, "Using Stereo for object Recognition", *International Conference on Robotics and Automation (ICRA), Anchorage, Alaska, 2010*.

[10] Lowe, David G., "Three-dimensional object recognition from single two-dimensional images," *Artificial Intelligence, 313, 1987, 355-395.*

[11] D. Lowe. "Distinctive image features from scale-invariant keypoints". *IJCV, 60, 2004, 91–110.*

[12] Zoltan-Csaba Marton, Radu Bogdan Rusu, Dominik Jain, Ulrich Klank, and Michael Beetz, "Probabilistic Categorization of Kitchen Objects in Table Settings with a Composite Sensor", *The 2009 IEEE/RSJ International Conference on Intelligent Robots and Systems, 2009, 4777-4784.*