International Journal of Engineering Trends and Technology
ISSN: 2231 – 5381 /doi:10.14445/22315381/IJETT-V69I9P219

Volume 69 Issue 9, 153-160, September, 2021

Resource Efficient Tool Recognition Approach Using Modified Shape Feature Extraction Technique for Robotic Vision Systems

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Abstract - *This paper discusses a resource-efficient hardware realization approach employing an improved shape feature vector for object recognition in the field of vision robotics. A modified shape signature method with less computational power is presented to analytically select the unique shape boundary points for 1D representation of 2D images. The robust real-time object recognition system is implemented using MATLAB and tested with the images of the KTH database for hand tools, which perform object localization irrespective of illumination and background settings. Results are further verified using an image set of robotic handling mechanical components, which are captured under their own experimental setup. Feature extraction utilizing Fast Fourier Transform and classification of the extracted vectors are analyzed.*

To discriminate between mechanical parts, containing nine classes and consists of fifty-four images, each captured under different background. Shape feature using FFT offers translation, rotation, and scale-invariant attributes, while improved shape signature ensures less dedicated hardware resource utilization, thus making the robotic vision module compact. The experimental results demonstrated that the proposed vision-based robotic system achieves an overall recognition accuracy with optimum utilization of resources. Thereby computational power required is less to an acceptable degree, and hence realization made easy.

Keywords — *Real-Time Robotic Vision Systems, Tool recognition, Feature extraction, Shape Signature, Machine Vision*

I. INTRODUCTION

This Vision-based robotic system for task execution is gaining high demand in the industrial sectors while processing speed, hardware structure compactness, as well as image quality issues are the key challenges in making these visual servoing systems compact. Robotic systems are used for industrial tasks like welding, painting, assembling/disassembling products, assisted material handling, complex visual inspection, and transportation tasks. These systems can take intuitive decisions intelligently in their structured environment by incorporating visual perception. However, vision-based processing is made challenging due to the association with entities of various sizes and shapes. In addition to the complications caused by the variety of the objects in images, the problems such as their interactions and occlusions, along with photometric variations in pose and size, can cause further deadlock. The real-time visual data processing must be incorporated for the proper functioning of vision modules so that they can act efficiently for quick adaption to the changes in its surrounding. Therefore a practical robotic vision module is in need of the best real-time and optimized performance.

Through extensive research work that has been carried out in real-time robotic vision systems, it still faces open issues like insufficient processing speed, accuracy, and lack of compactness. Existing systems are realized using software architectures that consume more resources and lack processing speed, thus making the hardware structures huge and complex. The shape-based object recognition is realized mostly using model-based approaches. These procedures commence by analyzing an ample set of images in different camera viewpoints and from different object poses. An object model is built
and learned a priori. Then the object features in the scene must be analogous with features of the previously developed object models. It is important to focus that the extracted features need to be robust and must be invariant to various transforms like camera direction, changes in illumination, and scale.

In most of the proposed methodologies, robotic vision-based workpiece identification is addressed by image processing and extracting features. The system developed has the capability to detect and recognize tools/components from a visual input image in real-time. In this work, using shape-based feature extraction, it is found that a logical selection of unique boundary points will overcome the disadvantage of large feature size requiring a substantial amount of storage space, thereby decreasing the computational power requirement. As such, the hardware realization is optimized employing minimum resources, and hence computational power requirement is minimized and can be easily realized. The approach can be applied to any robotic vision-based processing irrespective of position, orientation, scale, and varying illuminations.

There are varieties of robotic applications utilizing visual feedback in the industry sector. [1]–[3] Such systems are capable of detecting the object of interest from the images captured under background and lighting. These robotic structures use 2D views of different formats and sizes to make intelligent decisions for accomplishing the designated task. Objects from these two-dimensional views require a collection of features like color [4], shape [5]–[13], texture[14], etc., to be calculated. Though several features are available, the shape of the object is invariant to translation, scaling, and rotation, which makes it unique to be used as a feature for vision-based object recognition. Real-time images have to be processed to extract the object in the presence of background clutter and illumination variations. Several preprocessing methods [15] are available in the literature for removing noise, filling up the holes using morphological operations and edge detection. Once the images are processed properly, feature extraction is the key aspect of pattern recognition and deals with the most relevant information that can be used to characterize each class.

Shape feature extraction techniques are classified into region-based and contour-based [16]. An approach based on region/boundary represents global shape features which take each and every point on the shape is represented with Moment invariants, orthogonal moment descriptors like Zernike, Legendre, and Complex shape moments. The contour-based shape approach deals with the contour lines of the shapes in distinct forms, such as centroid distances, shape signatures, scale space methods, spectral transforms, and structural representation. The main limitations for boundary-based methods are lower-order moments vaguely depicts the shape, but moments of higher orders are hard to acquire and more sensitive to noise.

II. SYSTEM OVERVIEW

A modified technique that enables object detection and recognition in an environment of complex background settings and light variations is presented. The methodology adopted consumes fewer resources, thus making the module easily realizable as well as power efficient. The technique offers remarkable success in classification irrespective of variance in environment settings and has the following submodules, which are discussed as follows:

A. Image preprocessing

Multiple objects can remarkably intricate the recognition of each entity in an image. Real-time views of the entity that has to be recognized are distracted by the scene clutter. Likewise, in any image analysis, it is mandatory to perform basic operations like generating a binary image, removing the noise, image sharpening, and smoothening. A common limitation in the contour method is the presence of holes and detached parts of the shape, which is overcome by morphological operations to trace shape boundaries.

Image preprocessing is the most crucial step for extracting the object of interest from its background in the 2D views, as the shape feature vector used for identifying depends solely on how well the object is deciphered against its environment. Evaluation of the proposed feature extraction technique is done in two stages. Initially, images from the KTH database [17], [18] are processed to extract hand tools under non-consistent lighting and backdrop settings. In the second stage, a database system is constructed using a set of mechanical components captured under different background settings and processed to separate out each component for identification. Color images from the datasets are processed to get the threshold value for each color channel and for the generation of the binary mask. The mask so obtained can be used to draw out the desired tool against its distinct surroundings and illumination setting. An easy way to comply with the conference paper formatting requirements is to use this document as a template and simply type your text into it.

B. Boundary based corner extraction

Corner detection from the boundary can be applied over natural or binary images. Preprocessing enables for clean, connected edge field of the object periphery. The work [19] gives a computationally fast, simple, and efficient technique for corner detection based on boundary coordinates. The corner on a boundary curve is calculated from the expected
point for each point on its periphery.

Let **N** be the set of object coordinate points used to represent an enclosed boundary curve B.

$$B = \{pi = (x_i, y_i), \text{ for } i = 1, 2, \ldots N\}$$

In the above equation, p_i is the adjacent neighbor of $p_{(i+1)\mathrm{mod}\ n}$, and (x_i, y_i) corresponds to the Cartesian coordinates of p_i. Let $S_k(p_i)$ is the small curve segment (of B), its midpoint is p_i and is identified by the support region for the point p_i and can be mathematically denoted as

$$S_k(p_i) = \{p_j |\ j = i\text{-}k, \ldots i, \ldots i+k\}$$

The expected point p_{ie} for the boundary segment denoted by $S_k(p_i)$ is given by $p_{ie} = (x_{ie}, y_{ie})$ where x_{ie} and y_{ie} are the respective mean values for X and Y coordinates in $S_k(p_i)$ and are described by

$$x_{ie} = \frac{1}{2k+1} \sum_{j=i-k}^{i+k} x_j \qquad (1)$$

and

$$y_{ie} = \frac{1}{2k+1} \sum_{j=i-k}^{i+k} y_j \qquad (2)$$

Each point that is replaced by the expected value will smoothen out the periphery of the curve. Hence, the expected value for a corner will possess a shift much larger in comparison to further corners on the periphery. Hence for p_i, the cornerity index will be given by the Euclidean distance d between the points p_i and its expected point p_{ie} which is shown as

$$d = \sqrt{(x_i - x_{ie})^2 + (y_i - y_{ie})^2} \qquad (3)$$

The rank of a corner point is given by the cornerity index. The larger the cornerity index value for a point, it corresponds to a corner in the boundary. Figure 1 depicts the sample image of the screw in which the corners are extracted from the cornerity index calculated for all the boundary points in the object border.

C. Shape feature extraction

One of the visual features that can uniquely identify an object is the shape. Feature extraction based on shape and its representation is the foundation for object recognition in image processing. Shape representation is extracted using the boundary of the object and is denoted as

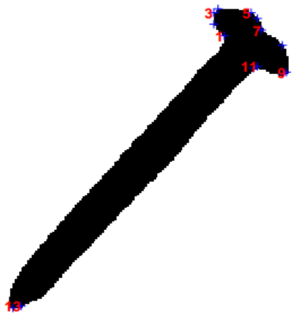
$$z(\mathrm{i}) = x(\mathrm{i}) + jy(\mathrm{i}) \quad (4)$$

where shape boundary coordinates (x(i), y(i)) , i=1,2,3…N-1 has been extracted in the preprocessing stage.

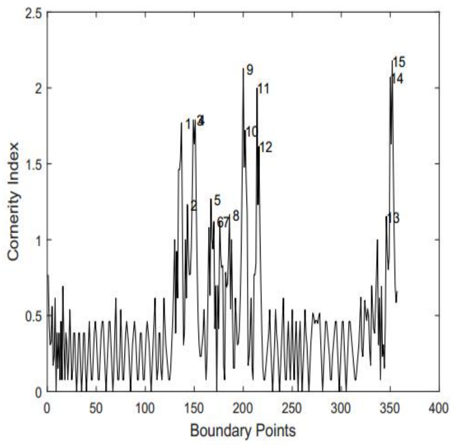
Shape signature is a 1-D function that can represent 2-D structures or object boundaries. It is a technique used for designating a unique shape and identifying the shape features. The Centroid distance r(t) is the commonly used shape signature for general shape representation, which is used with Fourier Descriptor,

$$r(t) = [(x(t) - x_c)^2 + (y(t) - y_c)^2]^{1/2} \quad (5)$$

The equation gives the distance of the boundary points (x(i), y(i)) with the shape centroid (x_c, y_c). Centroid is computed by the average of the boundary coordinates, as follows:



(a)



(b)

Fig 1: (a) Sample image with corners marked (b) its corresponding graph of cornerity index with boundary points

$$x_c = \sum_{n=0}^{N-1} \frac{x(N)}{N} \quad (6)$$

And

$$y_c = \sum_{n=0}^{N-1} \frac{y(N)}{N} \quad (7)$$

And N corresponds to the number of boundary points.

By taking the difference of centroid from coordinates of boundary, the calculated centroid distance will be translation invariant. Fourier descriptors thus extracted has the advantage of robustness to noise.

The proposed shape signature approach for the automatic identification of real-world closed contour objects in complex scenes is refined by the logical selection of the boundary points. Corners of each workpiece in the image are selected instead of the entire boundary points. This methodology is more promising for hardware realization in the sense that it captures optimum features and demand less computational time and resources.

Fourier descriptor is an extensively employed technique in shape analysis applications. Evaluating the Fourier transform of 1D shape signature gives the coefficients of normalized Fourier transform, which is otherwise known as the Shape Fourier descriptor. The discrete Fourier transform is calculated as:

$$a_n = \frac{1}{N}\sum_{t=0}^{N-1} \frac{z(u)}{N} e^{-\frac{ij2\pi nu}{N}}, \quad n = 0,1,\ldots.,N-1 \quad (8)$$

gives the n^{th} Fourier transform coefficient of z(u), also called Fourier descriptor of a two-dimensional shape and is denoted as FD_n = (a_0, a_1, . . ., aN_{-1}). By taking the magnitude values and by ignoring the phase information, the rotational invariance is obtained.

Invariance to scaling of the Fourier descriptor is attained by taking the ratio of the amplitude of the first half descriptor by the DC components (a_0).

$$FD = [\frac{|a_1|}{|a_0|}, \frac{|a_2|}{|a_0|}, \ldots\ldots\ldots \frac{|a_{N/2}|}{|a_0|}] \quad (9)$$

The chosen factor (a_0) is for scale normalization as it gives the average energy for the shape signature. In this proposed work, Fourier Transform is applied to improved shape signature, thereby reducing its complexity in computation. It is found that a reduced set for contour signature also preserves the property of its robustness to light variations and image transformations (scaling, rotation and translation).

D. Classification

The final stage of the vision module is done by the classification, which is accountable for object recognition using the extracted features.

The objective of the object classification is to identify the tool as a unique instance of the class. Our approach is to identify the tool from the surrounding background using the optimized set of shape features.

A tool (object) image *i* consists of a set of n member images $T_i = \{t_1, t_2, t_3 \ldots t_n\}$. Each class is represented and trained by a group of feature vectors. An image is said to belong to a particular class if the chances of its feature points being a member of that specific class are maximum. The probability is calculated using the Support Vector Machine (SVM) and K nearest neighbors (K-NN).

III. REALIZATION OVERVIEW

The proposed system is realized in MATLAB 2018b as a software tool in Windows OS. The algorithms for the object boundary extraction, unique identification of the feature points for its recognition and classification have been developed. The presented shape-based tool recognition architecture in Figure 2 starts with an image processing system, offline supervised training, and application to online tool recognition. The offline data analysis is made on tools found in the industrial domain in which multiple classes are categorized in accordance with common characteristics. Later it is used to train the detectors with a generated set of features from the object of interest in the images. The real-time online system uses the trained classifier model to analyze an unlabeled image in the system. The technique is applied and tested in the datasets-KTH dataset as well as an experimental setup developed at the laboratory. Former makes use of hand tools [26, 27] which were collected using the Yumi pedestal robot platform as part of the SSH FACT project. Dataset consists of images of hand tool objects of category- hammer, plier, and screwdriver took under different illumination and background as in Figure 3.

The results are further evaluated with another database system of mechanical components commonly used in the robotic industrial sector captured under different backgrounds. The background removal is a crucial step to extract the object/(s) from the image, which has to be done using suitable image processing methods or suitable API available. The basic steps involved in pre-processing are shown in Figure 4.

The work focuses on the logical selection of unique points of interest from the boundary of the objects in images, and such an analytical selection can reduce the resource utilization, making it efficient for low power hardware realization. As discussed earlier, corners as features are extracted from the boundary pixels. Figure 5 depicts the corners detected for an individual component separated from the multi-tool image of the experimental setup present in the chosen database. The results are studied with feature vectors calculated in three different approaches – with full boundary coordinates, with corners along the boundary as feature points, and a set of adjacent pixels along with the points of interest as features.

In the first approach, the feature vector is computed using the entire boundary coordinates as the points of interest. The last two approaches suggest improved methods in making optimum utilization of hardware resources where unique corners of the object (job) are analytically chosen as the points of interest. Such a logical selection of corners is made from the tool frontier coordinates, as explained earlier. The shape signature corresponding to the object (say mechanical component) is computed by the distance between the object centroid and each of the boundary pixels. Hence shape signature gives the 1D representation of a 2D view as in equation (4).

Estimating the FFT of this 1D shape signature gives the feature vector, which is used for training as well as classification. A set of an equal number of adjacent pixels from both sides of the unique corner are

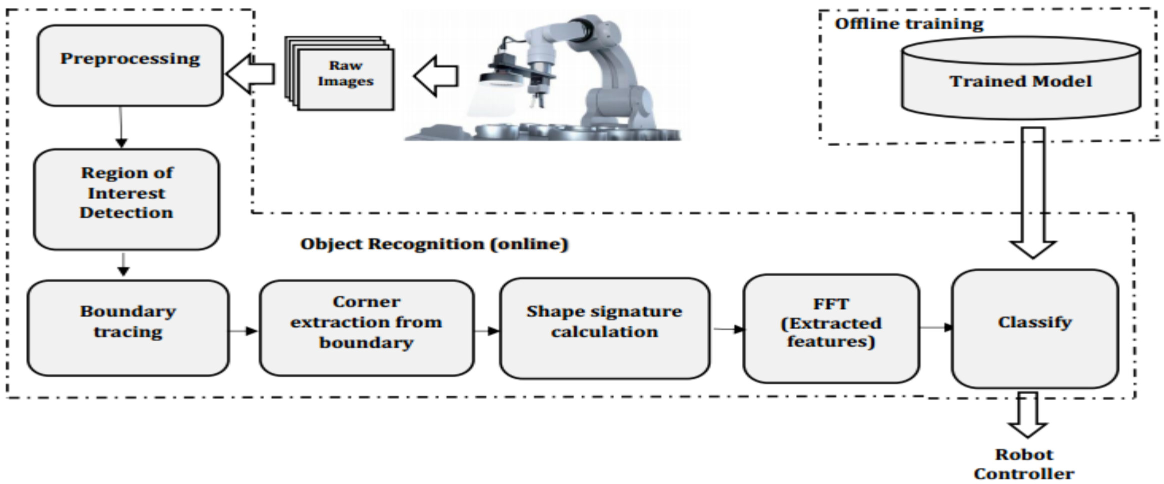


Fig 2: Block diagram showing the online training and offline object recognition stages of the proposed feature extraction module

Chosen to generate the shape signature for the object in the last approach. Such a set of corners as the point of interest not only gives considerable savings in the number of resources required for storage but also provides an appreciable accuracy in comparison with the feature determination employing the entire edge coordinates.

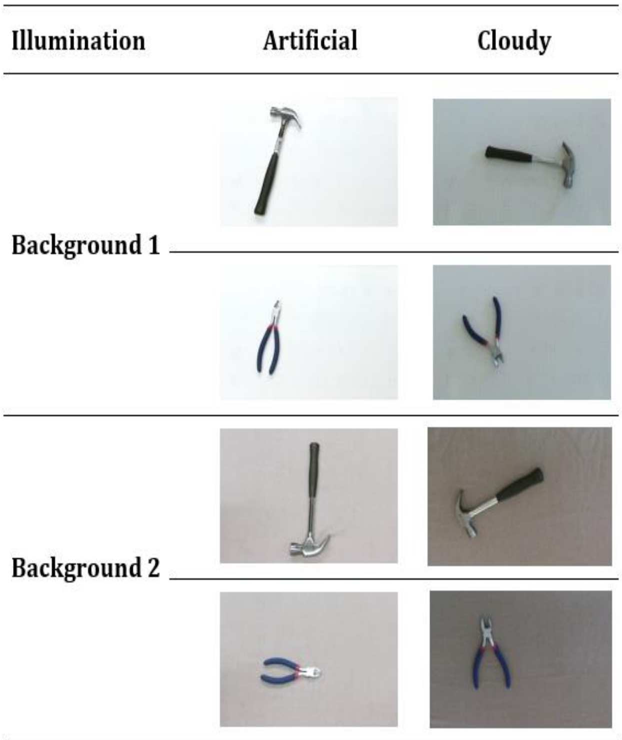


Fig. 3. Sample images of the KTH database captured using the Yumi Pedestal Robot

The feature vectors so calculated for the hand tool of the KTH database as well as for the database consisting of mechanical components under different illumination and background setting are translation, rotation, and scale-invariant.

IV. Results and Analysis

Experimentation to demonstrate the optimum hardware resource utilization of the proposed improved shape signature algorithm is performed on two datasets, as discussed earlier. Evaluation from the KTH dataset used 640 images divided into 8 different classes with 40 images per class. Each of the datasets is captured under artificial and cloudy background. In the second dataset, the feature extraction techniques are tested with a set of industrial mechanical components like screws, nuts, gears, and Allen keys.

Each image in both the database is 640x480 pixels in dimension and in JPG file format. The proposed technique for hand tool/component detection and its recognition has been tested so that a methodological study of the resource utilization and accuracy was carried out for 2D views in a different background, illumination, etc. Eight different objects were used as targets in the KTH database: two hammer variants, three distinct pliers, and three different screwdrivers. Likewise, nine classes of mechanical components were employed, with three each from nuts, screws, gears, and Allen keys. Shape-based features are calculated for the images with different orientations and positions for each image.

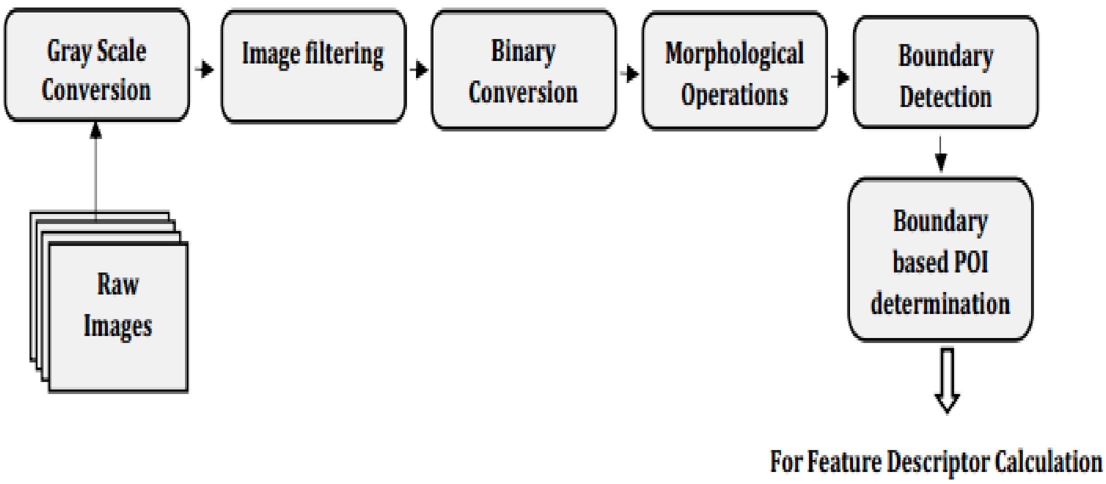
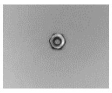
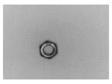
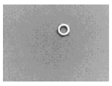
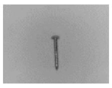
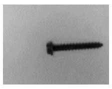
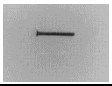
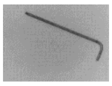
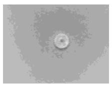
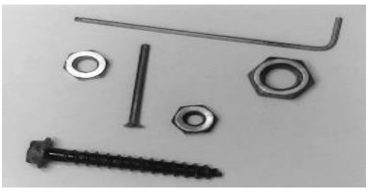


Fig. 4. Block diagram showing the image pre-processing steps adopted for the region of interest determination

TABLE 1. A FEW IMAGES FROM EACH CLASS AND THE CORRESPONDING RESOURCE UTILIZATION WITH DIFFERENT POINT OF INTEREST

Sl. No	Image	Point of Interest chosen for feature extraction				
		Scheme 1	Scheme 2		Scheme 3	
		Full Boundary (Pixels)	Corners (Pixels)	Pixel utilization compared with Scheme 1	Corner with adjacent points (Pixels)	Resource utilization compared with Scheme 1
1		209	18	8.61%	92	44.02%
2		289	35	12.11%	197	68.17%
3		217	48	22.12%	206	94.93%
4		429	10	2.33%	64	14.92%
5		725	127	17.52%	644	88.83%
6		401	13	3.24%	96	23.94%
7		1045	16	1.56%	92	8.98%
8		857	36	4.20%	126	14.70%
9		1089	80	7.34%	205	18.82%



(a)

(b)

(c)

Fig. 5. a) A sample image of mechanical parts b) Corresponding binary Image c) Binary image with POI marked

Table 2. Accuracy comparison using different approaches for different databases

Sl No.	Scheme	Accuracy (SVM)		Accuracy (K-NN)	
		KTH Database	Mechanical Component Database	KTH Database	Mechanical Component Database
1	Corners	70.5%	75.78%	62.5%	70.48%
2	Corners with 5 adjacent points	79.2%	79.22%	71.8%	78.88%
3	Corners with 10 adjacent points	81.4%	80.90%	75.3%	85.20%
4	Full Boundary	87.2%	86.16%	79.5%	87.06%

Each image in both the database is 640x480 pixels in dimension and in JPG file format. The proposed technique for hand tool/component detection and its recognition has been tested so that a methodological study of the resource utilization and accuracy was carried out for 2D views in a different background, illumination, etc. Eight different objects were used as targets in the KTH database: two hammer variants, three distinct pliers, and three different screwdrivers. Likewise, nine classes of mechanical components were employed, with three each from nuts, screws, gears, and Allen keys. Shape-based features are calculated for the images with different orientations and positions for each image.

Each image is input for preprocessing and feature extraction. Once the preprocessing was performed properly for each cue, the shape boundary could be easily extracted from the desired object even in the presence of other elements such as light variation, clutter, or shadows. The feature vectors are calculated using the state-of-the-art technique of full boundary points, and comparison was done against corners as a point of interest which are found from the shape edges. A correlation between the resource utilization was done using these schemes, as shown in Table 1. Employing full boundary points for feature vectors consumes a substantial amount of hardware resources for storing the entire boundary coordinates as feature points. The amount of storage required can be significantly reduced by the rational selection of corners while realizing in hardware platforms. Corners with adjacent pixels also offer efficient resource utilization, which can achieve accuracy as par with the full boundary points. This can be substantiated as follows: A sample image from the database (say image 1 in Table 1) has a total of 209 pixels for describing its periphery, and hence feature vectors will also have a similar size. The proposed approach identifies a set of 18 logical corners, which requires only 8.6% storage space in comparison with the first scheme. Though employing the third technique utilizes 44.02%, which still requires lesser resources, it attains an accuracy as par with the full boundary. Lesser resources make the entire module power efficient as well as compact

Table 2 compares the obtained results with different schemes for evaluating features: Corners, corners with 5 and 10 adjacent pixels, and full boundary in both the two databases.

As can be observed from the results, the improved techniques substantially attain an accuracy with the full boundary feature extraction scheme. The overall accuracies are plotted against the Fourier coefficients for classifiers Support Vector Machine (Figure 6 and Figure 8) and K -Nearest Neighbors (Figure 7 and Figure 9). Likewise, similar results are obtained with the KNN classifier as well.

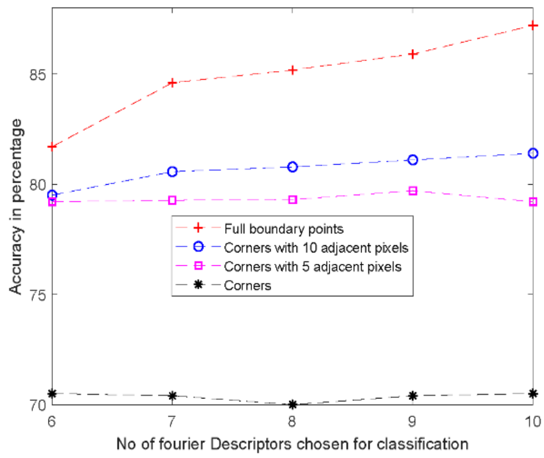


Fig. 6. Accuracy plot for different point of interest using SVM classifier for KTH database

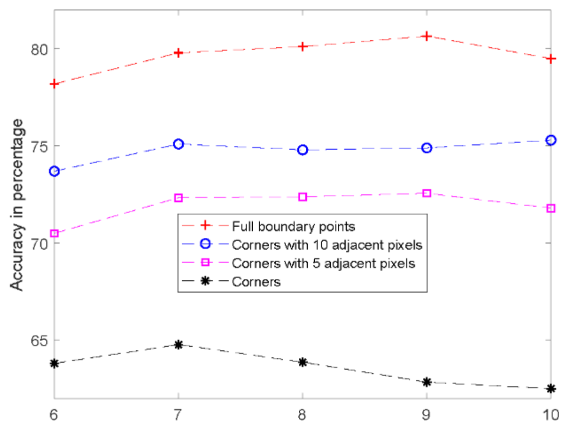


Fig. 7. Accuracy plot for different point of interest using K-NN classifier for KTH database

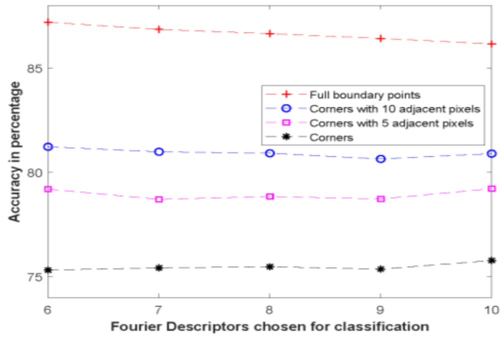


Fig. 8. Accuracy plot for different point of interest using SVM classifier for mechanical components

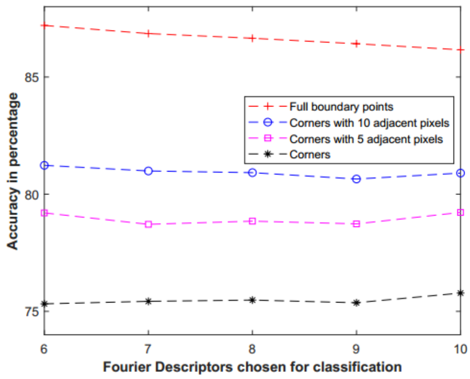


Fig. 9. Accuracy plot for different point of interest using K-NN classifier for mechanical components

V. Conclusions

The development of object recognition with optimized resources under various lighting conditions was based on the shape-based geometric features. The benefits of the proposed system, among others, include:

- The improved shape signature achieves a considerable accuracy of 81.4%; comparatively, it is efficient for similar vision based applications.

- The combination of an online 2D vision system with offline data for the calculation of 2D point of interest feature points allow for a significant decrease in the resource utilization, consequently making the vision module compact and easily realizable with less computational power.

The image preprocessing step has to be appropriately customized so that feature points will be adequately identified. These kind of vision systems are still a challenging problem when handling real time scenarios. The problem is due to the presence of varying cluttered backgrounds along with interactions in its industrial environment. Future study will be emphasized on this system's implementation in hardware structures for carrying out the feature extraction along with other coordinate values desired for carrying out the functionality of the vision-based robotic module.

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