Comprehensive Study on Shape Based Feature Extraction

ShaluGupta[1], Harmanpreet Singh[1] and Y. J. Singh[2]

[1]Dept. of Computer Science, Baba Farid College, Punjab, India, shalu2324@gmail.com
[2]NIELIT, Guwahati, Assam, India, yjayanta@nielit.gov.in

***Abstract*—**Worldwide, digital image processing has produced a large number of images. Shape is a key visual property of an object that must be recognized in a digital image before it can be identified. Employing a shape feature, find an object in an image. Object recognition and computer visualization both heavily rely on feature extraction. To the knowledge of researchers, there have been several periods of research, but there isn't a strategy for feature extraction that is widely accepted. The form aspects of feature extraction approaches are used in this research to categorize them. There are several methods for extracting features, including form descriptors, global features, structural features, etc.

Keywords— ***feature extraction, image retrieval, object detection, shape descriptor.***

I. INTRODUCTION

Image processing is a method used to improve unprocessed images from sensors or cameras mounted on satellites and from everyday photography for a variety of uses. The following categories can be applied to digital images:

- f (x, y) 2D: 2D images are dependent on two coordinates in a plane.
- f (x, y, z) 3 Dimensional (3D) such as scan CT images
- f (x, y, t) for videos

Where f represents intensity (monochrome images) or color (color images) or other associated values.

Table 1: Image types with their processing

Type	Input	Output	Process
2D	Image	Image	Image processing
	Image	Data	Image Analysis
	Data	Image	Computer Graphics
3D	Image	Data	Computer Vision

As shown in table 1, Image alteration is the main focus of image processing. Image to image transformation is studied in image processing. In computer graphics, geometric objects are created, altered, and stored together with their images. The process of drawing out important information from photos is known as image analysis. Low level computer vision processes include feature extraction from an image, whereas intermediate level computer vision processes include object recognition and 3D scene representation. Additional conceptual descriptions of a scene, such as activity, intention, and conduct (High level Vision), are also included. Computer vision is the interpretation of an image's composition or structure.Image recognition is one of the main issues with image processing. An object in a picture is represented by a group of pixels.

One important step in the object detection process is feature extraction, which is utilized to quantify the pertinent shape that is present in an object. The extracted features have an impact on how well an object recognition system performs. The traits that are extracted could be structural or statistical in nature. By assigning it local and global attributes, structural features represent a pattern in terms of its topology and geometry. As statistical features, the characteristics of the distribution of pixel values on a digitized image are recorded. In this process, characteristics are extracted to produce some quantitative information or features. There are numerous applications that use feature extraction, including

- Character recognition (Optical Character Recognition)
- Document verification
- Reading bank deposit slips
- Extracting information from cheques
- Applications for credit cards
- Health insurance
- Loan, tax forms, tax reading
- Data entry, postal address reading,
- Check sorting
- Script recognition etc.

The object will then be classified or recognized using a classification technique that uses feature extraction as an input.

II. LITERATURE REVIEW

The accurate assignment of a picture to one of the potential output classes after receiving it as an input is one of the main tasks in image recognition. The three tasks of extraction, selection, and classification are often separated apart. "Features should contain information required to distinguish between classes, be insensitive to irrelevant variability in the input, and also be limited in number to permit, efficient computation of discriminant functions and to limit the amount of training data required," according to Lippman's criteria for feature extraction.

As shown in figure 1, there are three categories of operations that can be used on digital images to change an input image (a[m,n]) into an output image (b[m,n]) or another representation:

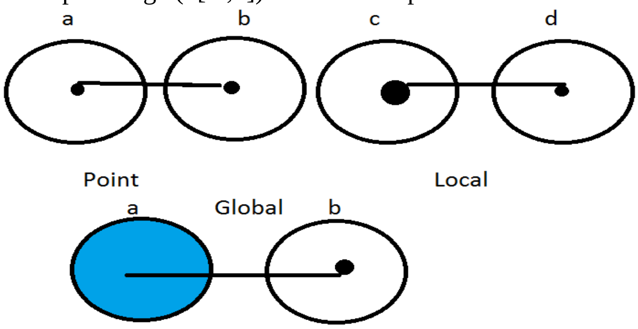

Figure 1: Various types of image operations

- Point: The output value $b[x_i, y_j]$ at a specific coordinate is dependent upon the input value $a[x_i, y_j]$ at that same coordinate and keeping complexity constant where i is row and j is column. Features are calculated at each pixel i.e. color, location etc.

- Local: The output value at a specific coordinate is dependent on the input values in the neighborhood of that same coordinate and complexity is P^2 (P X P is neighborhood size). Local operations produce an output pixel value of the specific coordinate pixel value in the neighborhood i.e. 4 connected neighborhoodsas shown in figure 2 (a)$a[x_i, y_j]$, $a[x, y_{j+1}]$, $a[x_i, y_{j-1}]$, $a[x_{i+1}, y_j]$, $a[x_{i-1}, y_j]$or 8 connected neighborhoodsas shown in figure 2 (b) $a[x_i, y_j]$, $a[x, y_{j+1}]$, $a[x_i, y_{j-1}]$, $a[x_{i+1}, y_j]$, $a[x_{i-1}, y_j]$, $a[x_{i-1}, y_{j-1}]$, $a[x_{i+1}, y_{j+1}]$, $a[x_{i-1}, y_{j+1}]$, $a[x_{i+1}, y_{j-1}]$.

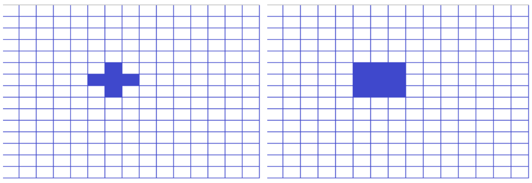

Figure 2: (a) Rectangular sampling of 4 connected pixels (b) Rectangular sampling of 8 connected pixels

Global: The output value at a specific coordinate is dependent upon all the values in the input image where complexity is N^2 ($N \times N$ is image size). Girshick *et al.* [1] integrate two major insights: (1) When labeled training data is insufficient, supervised pre-training for an auxiliary task, followed by domain-specific training, can be used to localize and segment objects by applying high-capacity convolutional neural networks (CNNs) to bottom-up area recommendations. The technique was known as R-CNN: Regions with CNN features because it combines region suggestions with CNNs. A regional contrast-based salient object detection technique was presented by Cheng et al. [2] that concurrently evaluated global contrast differences (which distinguish a large-scale object from its surrounds) and spatially weighted coherence scores. In order to obtain images using a greedy strategy, Nandgopalan et al. [81] propose combining three feature extraction techniques, such as color, texture, and edge histogram.

Yu [3] employed a shape code word called Triple-Adjacent-Segments (TAS) derived from picture edges, and object detection was carried out using a probabilistic voting mechanism. A shape codeword and a collection of related vectors that describe the object Centroid make up a shape codebook entry. The shape code words are simple and widespread, making it easy to separate them from the rest of effective object groupings. The geometrical relationships between the form code words, which define the properties of a specific object category, are stored in their related vectors.

Rangarajan et al. [4] offers an iterative approach to object representation that finds correspondences and deforms models at the same time. By alternately estimating the correspondences while maintaining a fixed transformation and computing the transformation while fixing the correspondences, the sum of the distances between model points and image points is reduced.

Zhong [5] introduced the Intrinsic Shape Signature (ISS), a new 3D shape descriptor to describe a local or semi-local region in a point cloud. An intrinsic shape signature uses a view-dependent transform recording the viewing geometry to speed up pose estimation and an independent view representation of the 3D shape to match shape patches from various perspectives directly. Both highly discriminative form matching and effective pose estimation and registration for 3D point clouds are made possible by the ISS technique. Additionally, they offer a highly effective indexing method for the high dimensional ISS shape descriptors, enabling quick and precise searches across sizable model databases.

Golovinskiy [6] created a system that consisted of the following four steps: finding, segmenting, describing, and categorizing clusters of 3D points. To be more precise, they used hierarchical clustering to first group neighboring points into a collection of likely item positions. They then used a graph-cut method to group nearby points into the foreground and background sets. Then, for each point cluster, they created a feature vector (based on both shape and context). An array of options were offered for each step when they labeled the feature vectors using a classifier that had been trained on a set of manually labeled items. In a portion of the scan of Ottawa that had around 100 million points and 1000 objects of interest, they statistically assessed the system and tradeoffs of several possibilities.Yang *et al.* [7] divided these techniques into four groups: appearance-based methods, knowledge base methods, template matching methods, and feature invariant approaches.

Zhu *et al.* [8] Develop an incremental concave, convex approach (iCCCP) that enables effective learning of both two and three layer models. They demonstrate that iCCCP produces a straightforward training algorithm that does not require extensive initialization, sophisticated multi-stage layer-wise training, or careful part selection to obtain good performance. When tested on challenging public PASCAL datasets, they successfully execute object detection using learnt models and achieve performance commensurate with cutting-edge techniques.

Lowe [9] The Scale Invariant Feature Transform (SIFT), which extracts a considerable collection of feature vectors that are robust through a wide range of affine distortion, the inclusion of noise, and partial invariance to changes in illumination. The maxima and minima of the Difference of Gaussians (DOG) method's output are referred to as key points. SIFT makes it possible to choose the best match for a key point from a big database of other key points. Orientations are given to localized key points after low contrast participating candidate points and edge reply points with an edge are eliminated.Bay *et al.* [10] introduce Speed Up Robust Features (SURF), a unique interest point detector and descriptor that is scale- and rotation-invariant. They put up plans for robustness, distinctiveness, and repeatability.

Singha *et. al.* [11] Wavelet transformation and color histogram are used to extract the texture and color features, and a combination of these features is then utilized to scale and translate an item in an image. They employ color space selection, quantization, and a color histogram for the color feature. They employ the Haar Discrete Wavelet Transform for the texture feature.

Toshev *et al.* [12] introduced the chordiogram, a novel shape descriptor, and boundary structure segmentation (BoSS), a shape-based approach for segmenting and recognizing objects. A chordiogram depicts both the inner and exterior of an object. In contrast to perceptual saliency cues, which are perceived as coherent zones that are distinct from the backdrop, a chordiogram depends on geometric associations of object border edges. The peak, valley, and curvature principles underlie the shape-based histogram. In the event that the image is multimodal, the valleys can be used to choose thresholds [13]. Nunes *et al.* [14] enumerate the many image retrieval features, including solidity, axis ratio, area ratio, perimeter ratio, eccentricity, extension, and invariant moment, among others.

Sobottka*et. al.* [22] used color and shape information for robust segmentation of faces. Facial feature tracking is performed by block matching. Liu *et. al.* [23] proposed aspect ratio adaptive normalization (ARDN) and compared 10 normalization functions out of which seven are dimensions based and 2 based on moments and eight feature vectors on three distinct data sources. Aquino *et. al.*[24] proposed template based methodology for segmenting optic disc from digital retinal images. Reed *et. al.* [25] investigated the different texture segmentation methods, such as boundary-based methods, region-based methods, statistical features, and operator-based features. Silva *et al.* [15] presented technique built on a saliency detection multi-scale spectral residual (MSR) analysis. Compared to a typical picture search using a sliding window [16].

III. FEATURE EXTRACTION

The purpose of image representation is to improve the accessibility of object information for computer interpretation. It comes in two flavors: using the region's boundary (external characteristics) and using the region's pixels (internal characteristics). In order to extract exterior characteristics, boundary descriptors are helpful. It comprises shape numbers, Fourier descriptors, Statistical Moments, and geometrical descriptors (such as diameter, parameter, eccentricity, and curvature).

Extracting internal characteristics is made easier by using regional descriptors. It consists of texture, moment of 2D functions, and geometrical descriptors (such as area, compactness, Euler number, etc.). The following are the many feature types:

Color Features: Color is professed by humans as a combination of threecolorsstimulates i.e. Red, Green, Blue, which forms a color space [21].The color property is one of the most widely feature used as visual features. Color features have many advantages such as robustness, effectiveness, Implementation and computational Simplicity, low storage requirements etc. It can be extracted from various methods such as: Histogram Model, Color Model and Statistical Model etc [17].

Color Histogram Model: In this approach the number of given color pixels are calculated as histogram extraction which involves the following steps i.e.Cells are partitioned according to their colors.Create a histogram bin on the basis of association of each cell.

Color Model: Maincolor models areused for feature extraction are as follows such as:

RGB (Red, Green, Blue): RGB colors are called primary colors and additive colors. With the combination of these colors we can obtain other colors such as CMYK (Cyan, Magenta, Yellow and Black) and HSV (Hue and Saturation value).

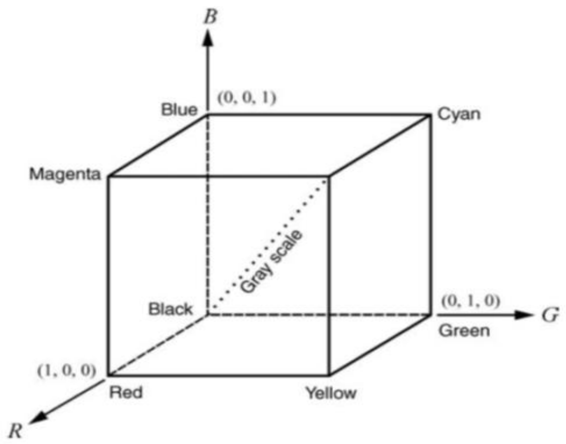

Figure 3: RGB color space

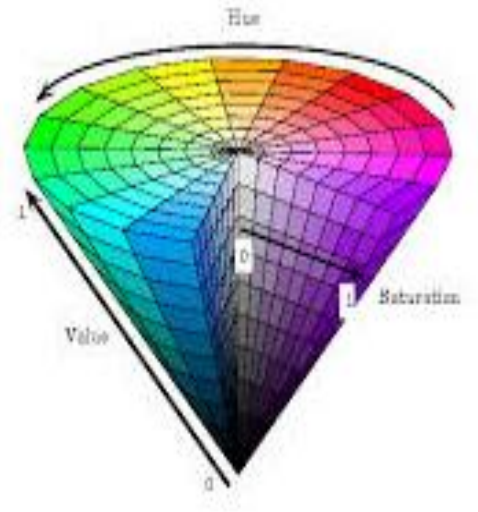

Figure 4: HSV color space

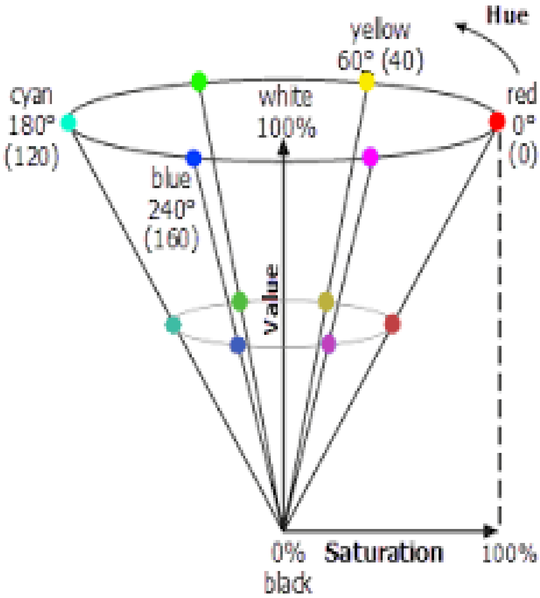

Figure 5: CMYK color space

Gabor Filters: Gabor function includes complex exponential such as cosine or sine function and localized around x = 0 by covering with Gaussian window shape [10].

Shape Based Features: It is the measuring of similarity between shapes. Shape descriptor features are computed from objects contour i.e. aspect ratio, circularity, length irregularity, complexity, sharpness, translation, rotation etc. Shape descriptors are partitioned mainly into two categories i.e. Region based (whole area of an object) and contour based (information present on the contour of an object) methods.

Table 2: Classification of shape representation and description techniques.

Shape			
Contour Based		Region-Based	
Structural	Global	Structural	Global
Chain Code Polygon Split Merge B-spline Invariants	Perimeter Compactness Eccentricity Shape Signature Hausdoff distance Fourier Descriptors Wavelet Descriptors Scale Space Autoregressive Elastic Matching	Convex hull Media Axis Core	Area Euler Number Eccentricity Geometric moments Zernike Moments Pseudo-Zernike Legendre Moments Generic Fourier Descriptor Grid Method Shape Matrix

Contour Based Shape Representation and techniques: These methods can only make use of shape boundary information. These come in two flavors: global or continuous approach and discrete approach based on structure.

Structure Based Features/Discrete approaches: This method uses a certain criterion to divide the shape's boundary into segments known as primitives. The final representation is either a string or a graph (or tree), and similarity measures are carried out using text or graph matching.

Chain code:A contour is represented as a series of straight line segments with specific length and orientation using this boundary representation technique. The steps for construction chain codes are as follows:

• Choose a starting point for the boundary and represent it in the image using absolute coordinates

• Show the transition from one point to the next on the boundary by representing each subsequent point with a chain code

• Stop if the next point is the starting point or the boundary's end

Polygon Approximation: An easy way to see the border of a planar object is with a polygonal approximation, which is the boundary defined by a collection of linked line segments.

Split Method: In this, an object's boundary is divided into a number of tiny segments, each of which is represented by a straight line. It is a top-down strategy. The split approach involves the stages listed below:

• To move a line segment up to the boundary's connected end points, and if the boundary is closed, to take into consideration that line segment's connection to the two furthest locations.

• To identify the boundary point that is furthest from the line segment.

• If the distance is more than the threshold, create a new vertex and divide the segment into two.

Repeat the same procedure for each of the two sub segments until the distance is below threshold.

Merge Method: Itoperates in opposite direction of splitting method. It is bottom-up approach. Following are the steps for merge method:

- Use first two boundary points to define a line segment
- Add a new point if it does not deviate too far from the current linesegment
- Update the parameters of the line segment using least-squares
- Start a newline segment when boundary points deviate too farfrom the line segment.

Shape Invariants:A unary invariant is with one or single feature. A binary invariant is with two features. A ternary invariant is with three features and so on. Geometric invariants include cross-ratio, distance ratio, length ratio, angle, area and triangle [33],common invariants from coplanar points [35]; algebraic invariants such as determinant, eigenvalues [32], trace [35].

Global or Continuous approach: This approach does not partition the shape into sub-parts, it usually extracts the features of integral boundary of an object which are further used to describe the shape of an object. The shape similarity is measured by metric distance by comparing the acquired feature vectors.

Perimeter: Perimeter of an object includes the perimeter of any interior holes of an object.

Compactness: To compact an image for improving the performance.

Eccentricity: It measures the shortest length from a known vertex to arrive ata certain vertex of a connected graph. It is the ratio of major axis to minor axis.

Shape Signature: Signatureis a ID representation of a boundary. It represents shape by one dimensional function which derived from shape boundary points. Shape signatures include centroid points and distance, complex coordinates, tangent and cumulative angle, curvature, area and chord-length. Signatures are invariant to location i.e. rotation variant and scale variance.

Hausdorff Distance: Hausdorffdistancehas been used to find objects in an image and determinerelationship between shapes.

Fourier Descriptors: It is to traverse the pixels relating to a boundary and it starts from an arbitrary point and record their coordinates.

Each value in the resulting list of coordinate pairs (x_0, y_0) , (x_1, y_1), … , (x_{K-1},y_{K-1}) is then interpreted as a complex number $x_k + jy_k$, for k = 0, 1, . . . , K − 1.The inverse it restores the original boundary.

The discrete Fourier transform (DFT) of this list of complex numbers is theFourier descriptor of the boundary. Fourier Descriptors has mainly translation, rotation and scaling properties.

Figure 6 shows a K-point digital boundary in the x-y plane and the firsttwo coordinate pairs, $x0$, $y0$ &$x1$, $y1$.

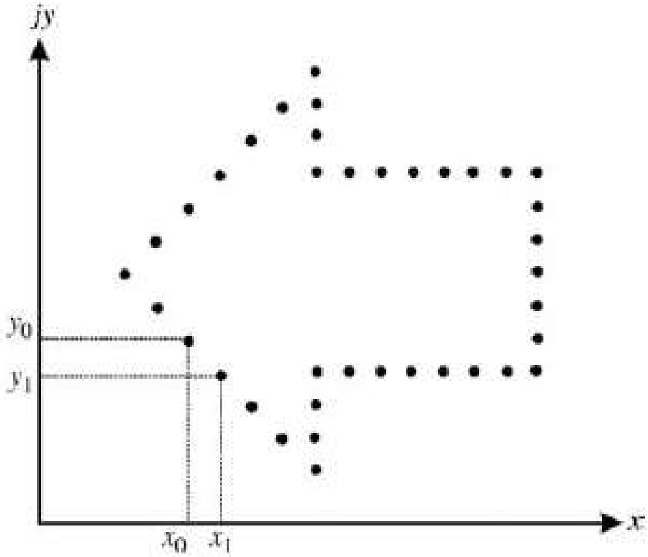

Figure 6: Fourier Descriptor of a boundary

Fourier Descriptor is backed by the well-developed and well-understood Fourier theory. The advantages of FD over many other shape descriptors are (i) simple to compute; (ii) each descriptor has specific physical meaning; (iii) simple to do normalization, making shape matching a simple task; (iv) captures both global andlocal features [29].

Wavelet Descriptors: It is also known as signal analysis method. It used periodical angle function on the basis of the Mexican Hat and Haar wavelet. Wavelet descriptor details related to the following significant points.

(i). Applying angle function: In some cases, it hides some sources of error, e.g. concave or convex object shape. (ii) Derivation of the formulas for the Haar wavelet descriptors (iii). Derivation of the formulas for the Mexican Hat wavelet descriptors. (iv). Performance assessment using minimum distance matrix. (v). Performance assessment compared to Fourier descriptors [31].

Scale Space: It is the representation of a shape and which is createdby tracking the position of inflection points in a shape boundary filtered by low-pass Gaussian filters of variable widths.

Elastic Matching: Bimbo *et. al.* proposedthe use of elastic matching for shape based image retrieval [36]. Deformedtemplate is computed as sum of original template τ(s) andwarping deformation θ(s).

$$\varphi(s) = \tau(s) + \theta(s)$$

where $\tau = (\tau_x, \tau_y)$ is a secondorder spline and $\theta = (\theta_x,\theta_y)$ is the deformation.

Aspect Ratio:is the width and length of normalized image. Aspect ratio of the normalized image is adaptable to the original image. It determines the size and shape of an image [22].

Region Based Features: Instead of using boundary information in this, all the pixels are taken into account to obtain the shape representation. Moment descriptors, such as the grid technique, form matrix, convex hull, and media axis, are used by region-based features to characterize shapes.

Structure Based Features:

- **Convex Hull:** A region R is convex if and only if the entire line segment x1x2 is included within the area for any two locations x1, x2 R [35]. The smallest convex region H that meets the requirement R H is referred to as a region's convex hull. The convex deficiency D of the area R is the name given to the difference H R [35].
- **Medial Axis:** Region skeletonization can be used for shape description and representation, just like a convex hull. A connected network of medial lines running the length of the limbs is referred to as skeletonization. For instance, while writing or drawing thick characters, the skeleton may be interpreted as the actual path taken by the pen.
- **Global:** The shape boundary information is typically used to create a multi-dimensional numeric feature vector through global contour shape representation approaches. The procedure of matching shapes is simple and is often carried out by utilizing a metric distance, such as the Euclidean distance or the city block distance. In some applications, point-based matching (or point feature-based matching) is also employed.
- Area, circularity (perimeter2 = area), eccentricity (length of main axis/length of minor axis), major axis orientation, and bending energy are some examples of typical shape descriptors [2].
- **Zernike Moments:** Orthogonal A unit circle encircling the polar coordinate space is known as a Zernike polynomial. In terms of difficulty computation, representation of compactness, retrieval, and resilience performance, it is the best descriptor for identifying related shape-based characteristics. Shape is a key aspect of a picture that can be used for applications including image analysis, object recognition, and image filtering [30], [38]. The fact that orthogonal moments convey shape invariants under translation, rotation, and scaling, as well as having some additional qualities that make them more resistant in the face of picture noise, is particularly important for image retrieval.

IV. CONCLUSION

Review of feature extraction approaches is presented in this study. The majority of feature extraction approaches rely on human input. It is important to research and evaluate new technological developments as well as existing ones. In this research, we investigate different feature extraction methods that focus more on shape than color or texture. To the knowledge of researchers, there have been several periods of research, but there isn't a strategy for feature extraction that is widely accepted. Numerous elements, including texture, form, color, spatial properties, homogeneity of images, etc., have an impact on the feature extraction of an image.

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