GEOMETRIC 2D SHAPES RECOGNITION WITH POLAR SIGNATURE CHARACTERIZATION AND TEMPLATE MATCHING

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ABSTRACT

This paper presents a proposed method for 2D shapes characterization and recognition by implementing polar shape signature and template matching algorithms. The motivation of this work is the advancement of robots and smart vehicles where robots need to perceive different kinds of shapes and signs and act accordingly. For example traffic signs recognition is a potential application for this research. Our proposed method was tested using 100 reference shapes and 50 testing shapes and were found to be robust and reliable at an accuracy of 95.83%. Furthermore, the method was tested using hand-drawn shapes and also found reliable with an accuracy of 95.45%.

INTRODUCTION AND RELATED WORD

In computer vision domain, object characterization and classification are very important stages that are considered main challenges in the vision process. Furthermore, characterization reliability and robustness highly influence object classification (Rababaah, 2005). In this paper we present an approach using polar signature for shape characterization then we use the template matching algorithm (Rababaah, 2011) to classify objects of 25 different 2D shapes. in the following section we present number of related work.

The work of (Torsello and Hancock, 95) presented a method for measuring the similarity between geometric shapes based on skeleton extraction of the 2D shapes. This measure is reported to solve some problems with 2D shapes characterization, clustering and classification. One important properties of this method is its ability to distinguish between similar objects with some structural differences. The authors reported that their method has been successfully tested a small set of shapes and yet to be verified with more statistically significant set. In (Mikolajczy et al., 2003), an approach is proposed to handle some challenges in 2D shapes applications based on edges. One of the strengths of this approach is that it is a model-based, where a model of an object is learnt by using a single image. Furthermore, this approach is reported to recognize objects in the same class. Two classes of objects were tested, bikes and rackets. The authors of (Chunjing et al., 2009) proposed a novel shape descriptor of planar contours. This new method represents the deformable potential at each point on the contour. This method accounts for global and local features of the shape. This new method is reported to perform reliably in shape matching applications. The work of (Rababaah and Shirkhodaie, 2008) presented a method for human posture classification. The contribution of this method includes extracting the perimeter of the posture shape and projecting it on vertical and horizontal axes to form a signal that characterizes the input posture. Template matching and hamming neural network were used to classify the human postures. The authors reported very reliable results of the proposed method.

METHODOLOGY

The proposed process is shown in Figure 1. The different stages are discussed hereafter.

Raw Color Image: the input image may have a single colored object or number of colored objects. The types of objects are focused on 25 different shapes for this study including several that are shown in Figure 1.

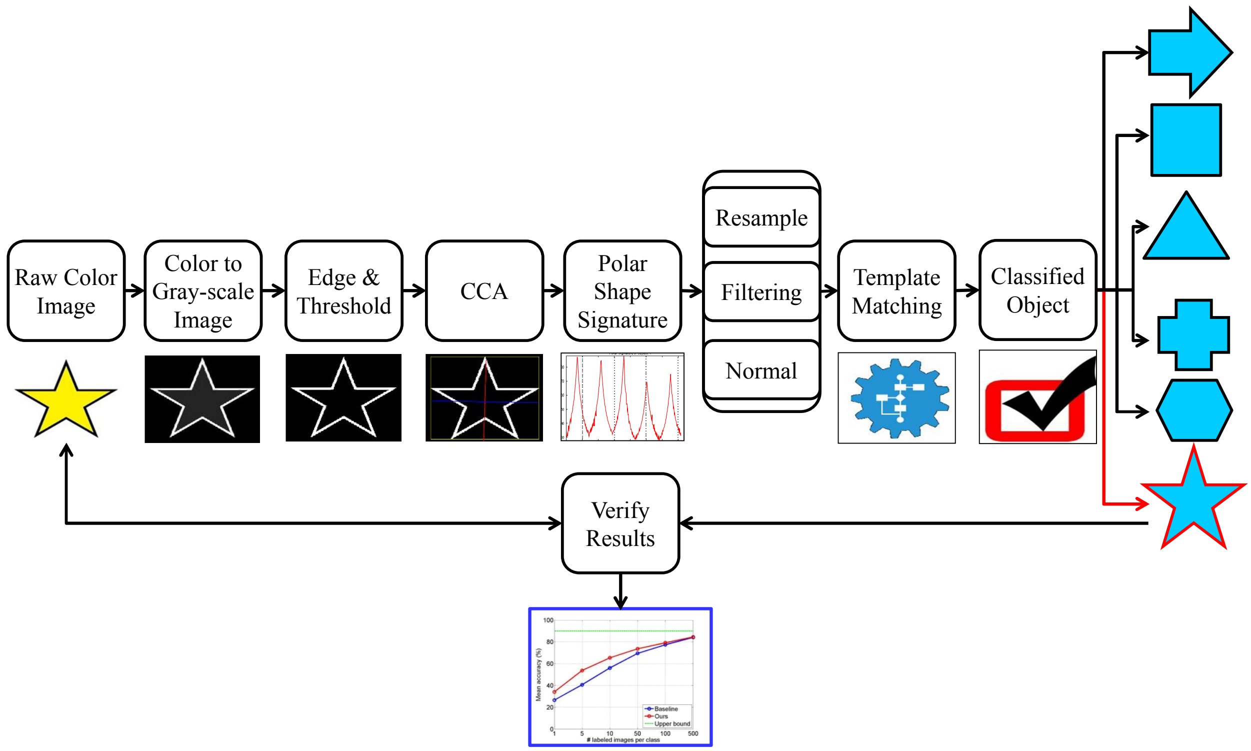

Figure 1: Process Block Diagram of the Proposed Approach

Gray-Scale Image: the colored image is transformed into gray scale or intensity image. This stage reduces the image color space from 24 bit to 8 bit color depth transforming the colored image to a 256 gray levels black to white extreme points. This stage is illustrated in Figure 2.

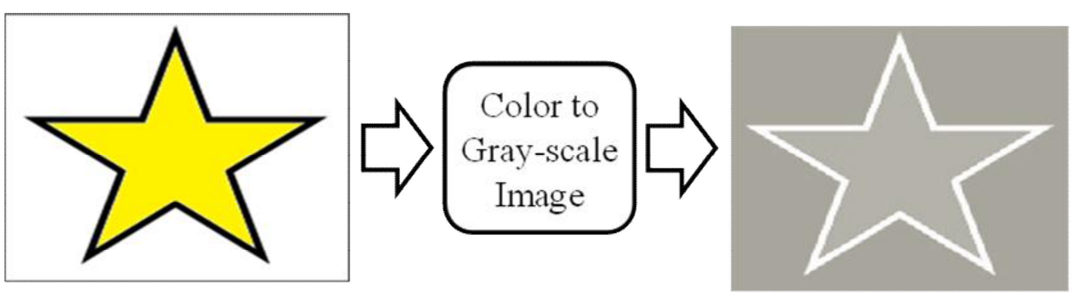

Figure 2: Colored Image to Gray Scale Image Transformation

Edge Detection and Intensity Threshold: As shown in Figure 3, the intensity image is converted to binary edges via edge detection the thresholding the edges to get a pure binary shape perimeter.

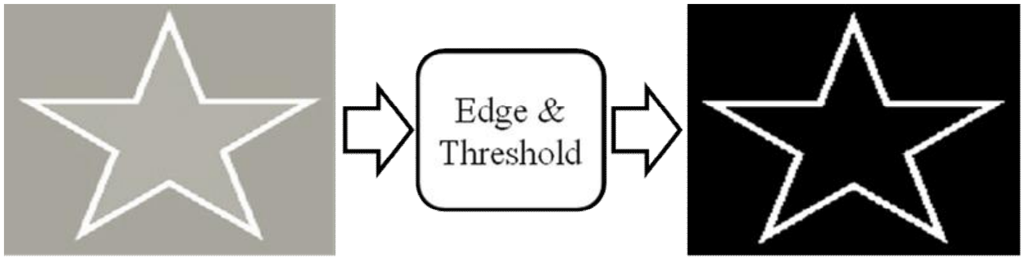

Figure 3: Extracting Object Perimeter via Gray Scale to Edge Detection and thresholding

Connected Components Analysis (CCA): this algorithm scans the binary image and labels the connected regions as separate objects. Once objects represented by the connected regions have been identified, each individual object can be visited and processed separately where, the geometric properties including: area, axes, orientation, eccentricity, boundary, etc. can be computed. More details on this algorithm is given in (Rababaah and Shirkhodaie, 2008). CCA is shown in Figure 4.

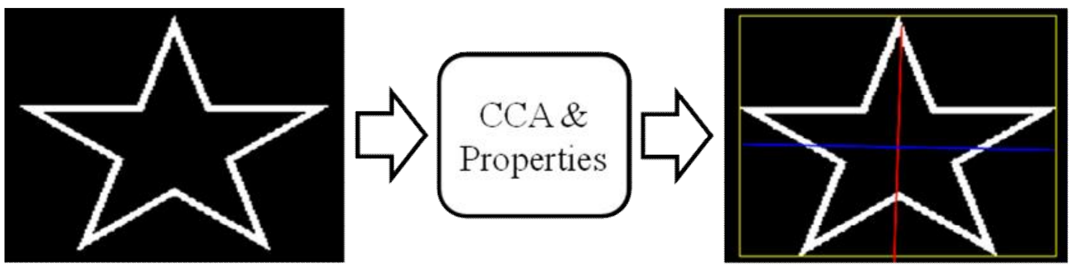

Figure 4: Connected Components Analysis and Properties of Shapes

Shape Polar Signature: this algorithm is a characterization method for 2D shapes that works by finding the centroid of the object and scans the object rotationally at a certain angle increment and at each angle it measures the radius from the centroid to the perimeter. The output of this algorithm is a signal that robustly characterizes the 2D shape to be used in classification algorithms. The reader is advised to review (Rababaah, 2009) for more details on this algorithm. A sample of this stage is demonstrated in Figure 5.

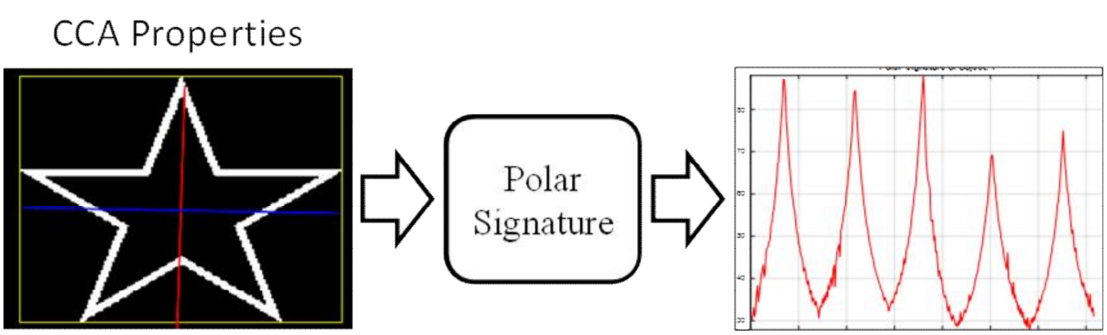

Figure 5: Shape Polar Signature after Connected Components Analysis

Resampling, Filtering and Normalization: resampling is a signal processing method that recuses the length of the signal while keeping the pattern to gain computational efficiency. Filtering is used to reduce any noise that may exist in the shape signature as it can be observed in Figure 6. Finally normalization is used to make all signals have to same range of amplitudes [0, 1]. This is achieved by dividing the signal by its max peak.

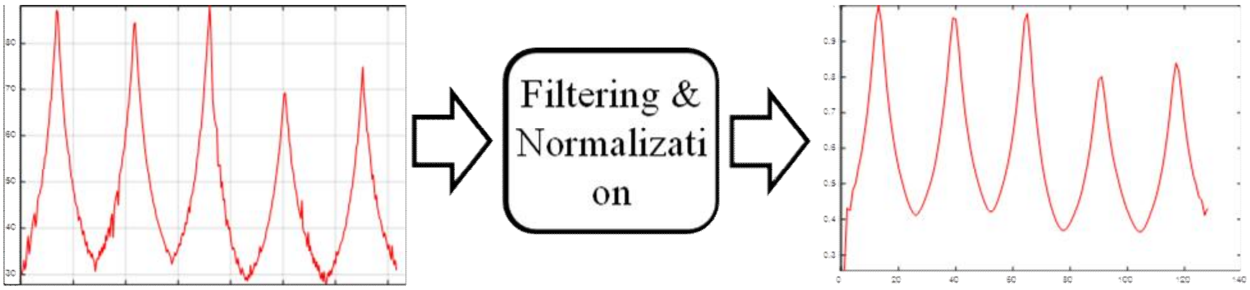

Figure 6: Signal Resampling, Filtering and Normalization.

Template Matching: this algorithm is an object classification method. TM is used here to classify the test data set of shapes into the reference set of shapes we described in the introduction. The algorithm starts by establishing a reference space of templates represented as vectors (signals) of the characterized shape models. A test shape after it has been characterized via a series of transformation operations as can be seen in Figure 1, it is fed to TM and number of similarity measures can be used including Euclidean distance and Coloration factor, etc. to match a target vector with closest reference vector. The algorithm is described below and copied from [6] with permission.

ALGORITHM: Template_Matching

1. Train matching engine by establishing a data set of reference templates

   $x_{ref}\ , x_i \in \{x_1, x_2, \dots, x_n\}$, where

   x_{ref}: the set of reference templates

   x_i : the i[th] reference template in the set x_{ref}

   n : number of reference templates in the set x_{ref}
2. Let y_i be the i[th] signal input to the template matching engine.
3. For each x_i in x_{ref},
   - 3.1 Compute the signal correlation factor ρ as in (4)
   - 3.2 Form a set (V) of voted templates with the pair (ρ_i, c_i), where, c_i is the class label of the reference template x_i.
   - 3.3 For each class in the x_{ref}, compute the sum of all ρ_is as the cumulative weighted votes for that particular class.
   - 3.4 Compare all of the cumulative votes (V_is) for each class and select the highest figure (V*) to be the most likely class label to be assigned to the input signal y_i.
   - 3.5 If the V* >= confidence level threshold, assign the input signal y_i the label of the winner class.
   - 3.6 Repeat step (2) while there are input signals

Finish

$$\rho = \frac{Cov(X_1, X_1)}{\sigma_1 \sigma_2}$$

Where,

$\rho =$ The correlation coefficient between the two variables X_1, X_2

$Cov =$ The covariance of the two variables X_1, X_2

$$Cov(X_1 X_2) = E(X_1 X_2) - \mu_1 \mu_2$$

E(x) = The mathematical expectation of a variable

$$E(x) = \int_{x \in S} u(x) f(x) dx$$

$\sigma =$ The standard deviation.

EXPERIMENTAL WORK

The proposed approach was tested by using 100 different images of shapes representing the 25 2D shape classes. Our approach is a model-based so; one reference template training image was used to register the model of the reference shape. Once the reference shapes have been registered, any unseen shape can be fed to the matching process and the closest reference shape is announced and returned as the class of the input image. Figure 7 illustrates for samples of how polar shape signature is extracted for 4 different shapes: square, triangle, left arrow and plus sign.

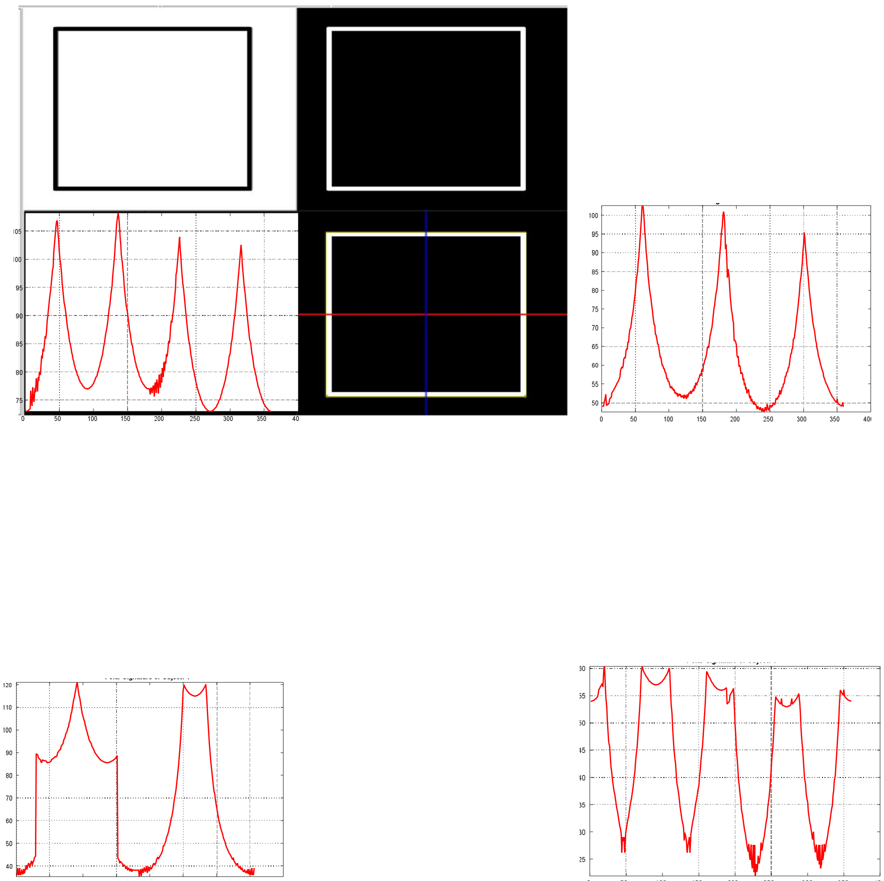

Figure 7: Shape Polar Signature for 4 shapes: Square, Triangle, Left Arrow and Plus Sign.

Figure 8 shows the final testing results of about 50 test shape samples. It is clear that these results demonstrate the reliability and robustness of the proposed approach with an accuracy of 95.45% and 95.83% classification accuracy.

CONCLUSIONS AND FUTURE WORK

We have presented a proposed approach for 2D shape characterization using shape polar signature. The approach applies a series of transformations on the input colored image to convert each shape object in the image to a 1D signal derived from the polar signature of that shape. For the classification phase, template matching was utilized to accomplish shape matching. The method proposed in this work was tested using about 50 different shape images and the results were very reliable and promising at a classification accuracy of 95.83%. Furthermore, it is worth mentioning that our approach is unique by using only a single image for establishing the reference model for each of the shape classes.

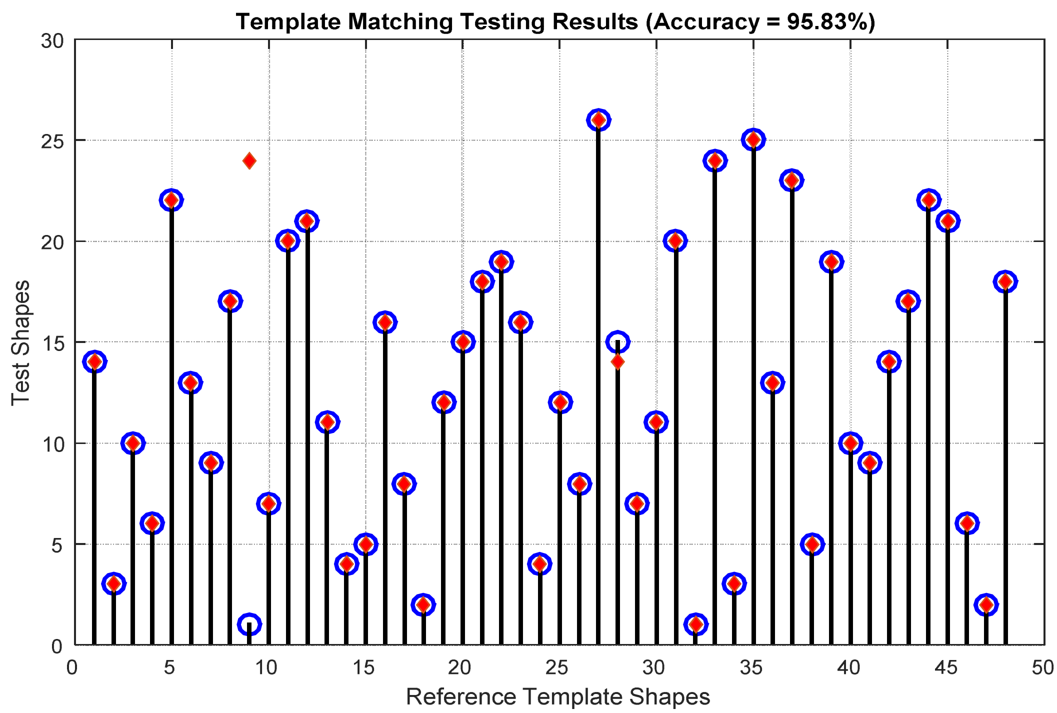

Figure 8: Final Testing Results of the Proposed Approach

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