Symbol Recognition using Particle Swarm Algorithms

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Abstract

Sketch recognition is defined as the process of identifying symbols that users draw using single or multiple strokes. Users draw strokes using a pen and the system should immediately interprets their strokes into objects that can be easily manipulated. This paper uses Particle Swarm Algorithm (PSO) to divide the strokes the user draws into meaningful geometric primitives. These geometric primitives are grouped to formulate symbols which are further identified. The results show that using PSO improves segmentation results which guide the symbol recognition phase. This paper uses SVM classifier which further improves the final recognition accuracy.

1. Introduction

Scientists generally and engineers specifically express thoughts and designs using sketches. Engineers use sketches to exchange designs as a natural method of communication rather than writing or speaking. Engineers use paper and pencil design in early stages of design. Design engineers need a powerful computer based system with symbol recognition to help them design, manipulate and store sketches more effectively than using only papers. Increasing the interaction between computers and users in sketch and CAD systems has been the reason for the emerging of few advanced sketch recognition systems [**?**]. Sketch recognition system converts the drawings and informal graphs user draws into objects and symbols that can be used in further interaction with the system.

Sketch recognition is divided into four main steps preprocessing, segmentation, symbol recognition and finally sketch understanding. The preprocessing process saves user input stroke points from the hardware and collects basic information about the stroke then proceeds to remove noise and primary data calculation. In segmentation phase, the system divides the stroke into a set of simple geometrical primitives or segments. The third phase, sketch recognition, is clustering strokes and segments to formulate symbols that can be recognized by a classifier system. Finally, the sketch understanding phase uses priori information about the sketch to support identification of symbols by excluding any possible invalid symbols. This paper introduces a sketch recognition system. The presented system uses' particle swarm algorithm (PSO) to optimally segment users strokes. Users can draw symbols using any number of strokes in any order they like. The system segments stroke user draws then cluster symbols together then passes them to the SVM symbol recognizer. The experiments in section 5 shows that the proposed system improves the final symbol recognition accuracy.

The remaining of this papers is organized as following; section 2 provides a brief literature review. Section 3 explains the general particle swarm algorithm which is used in the presented system. The proposed system block diagram along with a detailed system description is presented in Section 4. The experiments and results achieved are explained in Section 5. Finally, section 6 states the conclusion and future work.

2. Literature Review

The field of symbol recognition has gained interest in the last few years. A wide variety of techniques were used either on segmentation process or symbol recognition. A hybrid algorithm was introduced in [Sezgin *et al.*, 2001] where they generated different sets of segmentation based on both curvature and speed dominant points, this is followed by choosing a segmentation with the least error from generated hybrid set. Their system has a draw back as it only recognizes simple specific shapes with a set of low level recognizers. [Yu, 2003] introduced a feature area for each primitive and then computed the segmentation error for different types of primitives based on the computed feature area. Their system achieved good accuracy in simple shapes (square, ellipse,...) but did not perform well in more complex shapes[Yu, 2003; Paulson and Hammond, 2008]. Paulson and Hammond

[Paulson and Hammond, 2008] introduced a set of low level recognizers that were reported to achieve 98% accuracy but their system similar to all low level recognizers only identify a small set of simple shapes.

Many different approaches have been investigated to achieve final recognition of symbols. Graph searching and template matching where used in [Lee *et al.*, 2007] where a graph of the drawn symbol is generated and matched with a stored set of graphs templates to reach a classification decision. These systems may generate good performance but they are very computationally expensive. Geometrical and spatial descriptive language was used in [Alvarado and Davis, 2007; Hammond and Davis, 2003] where an architecture similar to compiler was used to recognize symbols. The drawback of this architecture is that the recognition system can only parse symbols that were hard coded using the descriptive language. New symbols are not recognized unless the description of the symbol is provided or generated using another system.

Genetic algorithm was used by [Chen *et al.*, 2003] to optimally divide digital curves into lines and curves. Chen *et al.* uses digital curves scanned from paper as input to the system and did not take advantage of the curvature or local geometric properties of the digital curve. Yin [Yin, 2004] used PSO to convert digital curves into polygons, our system adopts Yin method but improves it by adding curvature and other local information while segmenting strokes to achieve better segmentations. The next section presents the general particle swarm algorithm which is used in our proposed segmentation algorithms.

3. Particle Swarm Algorithm

The main idea of Particle Swarm Algorithm (PSO) is to represent each agent with a particle from the solution space. Each agent moves the particle with a direction and velocity based on equation 1.

$$v_{ij} = v_{ij} + c_1 r_1 (lbest_{ij} - p_{ij}) + c_2 r_2 (gbest_{ij} - p_{ij}) \quad (1)$$

where r_1 & r_2 are random variables and c_1 & c_2 are the swarm system variables.

$$p_{ij} = p_{ij} + v_{ij}, \quad (2)$$

where p_{ij} represent the jth particle in the ith agent and v_{ij} is the velocity of the jth particle in the ith agent. After each iteration the global best g_{best} particle and the agent local best l_{best} particle are evaluated based on the maximum fitness functions of all particles. The solution is found after achieving a specific number of iteration or after an error threshold is achieved. The following equation 3

$$P(i) \Leftarrow \left\{ \begin{array}{lll} 1 & if & r_3 > t \\ 0 & if & r_3 < t \end{array} \right\} \quad (3)$$

(where t is a threshold and r_3 is a random variable), is used in order to change the general swarm algorithm into binary particle which handles particle values of either 0 or 1.

4. System Details

Figure 1 shows that the main system blocks are 1) preprocessing, 2) segmentation, 3) clustering, 4) feature extraction, and finally 5) classification.

The preprocessing phase is responsible of capturing the input data and removing the noise from it. The system then proceeds to estimate a set of possible dominant points to help in the segmentation process.

The segmentation is divided into two steps ellipse fitting and curve segmentation. In the first step, the ellipse fitting process tries to fit the stroke into an ellipse. If the system fails, it passes the stroke to the second step; curve segmentation which consists of two PSO segmentation algorithms. The two algorithms generate two segmentations. The system then chooses the segmentation that has the minimum segmentation error.

The clustering algorithm starts to group segments together after the segmentation step. The system allows the user draws the symbol by using any number of strokes; a set of unrecognized segments is passed to the clustering algorithm to generate a symbol and compute a feature vector for it. A set of hybrid features of statistical, geometric and spatial features is used to generate the symbol feature vector. The final classification step, SVM classifier uses the feature vector computed to classify the segments into one of the previously trained classes. The following sections provides a detail description of each step.

4.1. Preprocessing

It is noted that as the user draws a shape, the pen slows down near corners and picks up speed when drawing a straight lines. Therefore, the speed and time difference data were widely used in sketch understanding systems [Sezgin *et al.*, 2001]. The direction and curvature data are used to determine the points with high angular changes along the path of points [Yu, 2003]. In the presented system, we computed time difference, direction, speed and curvature of each point along the stroke. The speed is calculated as $v = \Delta t / \Delta s$ where t is the time difference between two points and s is the length between them. The direction is calculated as

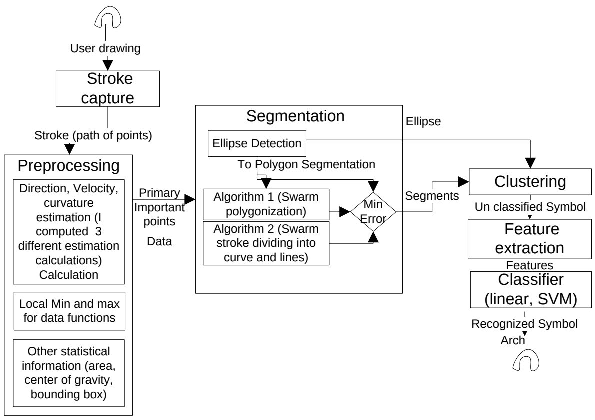


Figure 1. The system Block Diagram.
The figure shows the main system blocks. Preprocessing, segmentation, clustering, features extraction and classification.

the angle between two vectors and curvature is considered as the change in direction with respect to length i.e. $c = \Delta d/\Delta s$.

It should be noted that, all these calculations are performed in real time while the user draws the strokes. The complexity of computation is $O(n)$ where n is number of points.

Figure 3 shows the computed data for the stroke drawn in fig. 2. It is noted that the dominant points are characterized by lower speed values and higher curvature and direction values (fig. 3).

After the system computes all the speed, time difference and curvature data it proceeds to detect the points with low velocity and high curvatures. Using simple differentiations to detect local extreme points resulted in false points due to the non smooth curves. Hence, the system adopted a process presented by [Sezgin *et al.*, 2001], where the mean of the curve is calculated and used as threshold th. The threshold th is used to separate the curve into regions $Region_i$; each region $Region_i$ is defined as the part between two intersection points of the threshold line and the curve. Regions higher than the threshold th are processed to find the maximum point $Max(Region_i)$ of each region $Region_i$. The stroke points $p_i(x,y)$ that correspond to those maximum values are labeled as *possible dominant points* P_{pd}.

The system repeats this process to curvature, time difference and speed curves. All the points labeled as possible dominant points P_{pd} are saved into a single array. They are then used as input to guide the next segmentation phase.

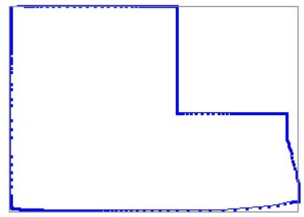


Figure 2. Stroke Sample
An example of the stroke drawn in the system.

4.2. Segmentation

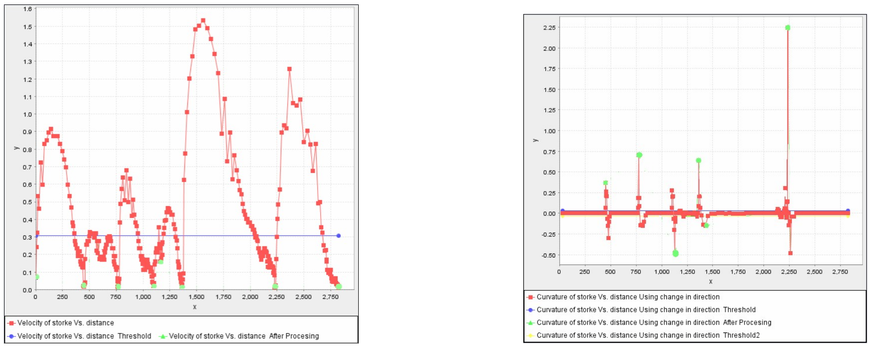
After computing the primary data the system tries to segment the stroke into a set of primitives. The segmentation algorithm first attempts to detect if the stroke is an ellipse. If the stroke proved to be an ellipse then the segmentation process ends and the system proceeds to the next step. Otherwise, the stroke is passed into two particle swarm algorithms that divides the stroke to either lines or lines and curves. The algorithms take the stroke points along with the possible dominant points P_{pd} computed then produce a set of dominant points which are connected with either lines or curves (see fig. 1). The next section describes the ellipse detection algorithm and the two particle swarm algorithms used to divide the stroke.

4.2.1. Ellipse Detection. The process starts by computing the center of the stroke bounding box. The bounding box center point is used as the first estimation of the ellipse center. The axes of the ellipse are estimated as $width/2$ and $height/2$ of the stroke bounding box. The least square fitting algorithm is used to minimize the fitting error of the ellipse equation eq. 4.

$$E = \sum_{i=0}^{N} \frac{(x_i - x_0)^2}{a^2} + \frac{(y_i - y_0)^2}{b^2} - 1 \qquad (4)$$

where N is the number of points in the stroke, a, b are the length of ellipse axes, x_0 , y_0 are the coordinates of the center point and x_i & y_i are the coordinates of point i in the stroke. After few loops, the error and a confidence values are computed to check if the stroke can be labeled as ellipse or not.

4.2.2. Discrete particle swarm algorithm (*DPSO*). Two DPSO algorithms are used to generate segmentations for each stroke the user draws. The segmentation with the minimum error value is chosen as the stroke segmentation. The problem definition is the same in



(a) The Speed of data (b) The Curvature

Figure 3. Data Curves

The curve in a) shows the speed of the points in stroke in fig. 2. b) Shows the curvature curve for the same stroke.

both algorithms but they differ in the method they use to compute fitness and error functions.

4.2.3. Problem definition. The input stroke with N points can be represented by set $S = \{x_1, x_2 \ldots x_N\}$ where x_i is the location of the point i. The swarm algorithms consist of M agents which are represented by the set $A = \{P_i \,|\, i = 1, 2 \cdots M\}$ where P_i is a single solution particle from the solution space. Each particle decodes the problem with binary array with the same length N as the input stroke. Therefore, the system represents each particle P_i by $P_i = \left\{p_{ij} \,|\, j = 1, 2 \cdots N\right\}$ where p_{ij} has only two values 0 or 1. When $p_{ij} = 1$ means that point j is a dominant point.

4.2.4. The algorithm. The fitness function and error calculation are different in each of the two *DPSO* algorithms. For the first algorithm *AlgS1*, the arc $\widehat{x_i x_j}$ is defined as the consecutive set of points from pointx_i to point x_j as in $x_i, x_{i+1} \cdots, x_j$. The line $\overline{x_i x_j}$ as the straight line connecting point x_i to point x_j. The approximation error is computed by the equation 5

$$E = \sum_{i=0}^{M} e(\widehat{x_i x_{i+1}}, \overline{x_i x_{i+1}}) \tag{5}$$

where M is the number of dominant points in this solution. The error $e(\widehat{x_i x_j}, \overline{x_i x_j})$ is computed as the sum of squared perpendicular distance from every point along the arc $\widehat{x_i x_j}$ to the line $\overline{x_i x_j}$.

The fitness is computed using equation 6

$$\max fitness(p_i) = \begin{cases} -E/\varepsilon N & if E > \varepsilon, \\ D/\sum\limits_{j=1}^{N} p_{ij} & otherwise \end{cases} \tag{6}$$

where N is the number of points in the stroke, D is the number of points in the solution that was previously labeled as a possible dominant point (P_{pd}), E is the computed error and ε is the error threshold. It should be noticed that when the error is larger than the threshold E the fitness is given a -ve value to lower the value of solution. Otherwise the system favors the lower number of vertices.

The second algorithm *AlgS2* has the same problem formulation but different fitness and error functions. It was previously introduced in [Chen *et al.*, 2003] but a genetic programming was used as the optimizing algorithm. The error of both circle and line estimation are computed for each segment $S_i = \widehat{x_i x_j}$, the approximation with the lower error value is the chosen approximation of this segment S_i. The sum of the approximation error of all segments is the total error of the particle. The error is computed by equation 7

$$E = \sum_{i=0}^{M} e(D_i) \tag{7}$$

where M is the number of segments in the solution, D_i is the minimum approximation error of curve and line approximations $min(d_c, d_l)$ as computed by [Chen *et al.*, 2003]. The fitness is computed by the equation 8

$$\max fitness(P_i) = \frac{1}{E \times M^k} \tag{8}$$

where E is the error and M is the number of segments and k is a parameter tweaked to get minimum number of segments.

Yin [Yin, 2004] used a merge and divide algorithm after each loop of the swarm system to refine the solution but this paper is introducing another enhancement method. After each loop of the swarm algorithm (*AlgS1* and *AlgS2*), each particle is refined using the following procedure. For each particle P_{ij} each dominant point is checked to find if it was labeled before as a *possible dominant point* P_{pd} (computed as in section 4.1), if it is not labeled the point is moved to the nearest labeled point. After that the particles are tested to make sure

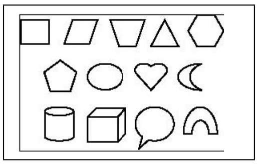


Figure 4. The Symbol Set
Ths figure shows a set of the symbols used in the dataset.

that the distance between every two successive dominate point is larger than the constant min_D. If two points are found that they are nearer than min_D then based on the decrease in the error E in eq. 5 & 7 one of the points are either removed or moved to the nearest possible dominate point.

4.3. Recognition

After the user draws all strokes of the symbol, he/she has to wait 10 seconds or press finish button beside the drawing area. The set of unrecognized strokes is grouped together along with their segmentation as input to the feature extraction process. A composite set of features is used to generate a single feature vector. The features used consist of Rubine feature set [Rubine, 1991], Zernike moments of order 21 [Hse and Newton, 2005], ink density [Gennari *et al.*, 2005] as well as some structural and spatial information like number of perpendiculars lines ,number of parallel lines and types of primitives in each symbol. After computing the features the symbol is introduced to the classifier. The system uses a support vector machine (SVM) classifier with Gaussian kernel (RBF kernel)[Chang and Lin, 2001].

5. Experiments

A dataset collected by Hse and Newton is used to test the presented system[Hse and Newton, 2005]. The data are drawn by 16 users each of them was asked to draw the 13 shapes from 30 to 50 times. Figure 4 shows a set of the shapes used in the data set. We divide the dataset into four sets each set contains four different users. We divide the dataset equally into training set and test set. To generate trusted results, four different splits for the training and test data are generated from the dataset. The results displayed are the recognition accuracy resulted from the classifier after recognizing the symbols. In the following section, the recognition accuracy means the average recognition accuracy in the four data splits. We performed two experiments to test the system firstly we tested recognition accuracy of shapes in the data set with both algorithms (*AlgS1* and *AlgS2*). We also implemented the segmentation algorithm described in [Sezgin *et al.*, 2001] (*Alg3*) to use as reference to our swarm algorithms. Figure 5 shows the accuracy achieved by each algorithm. The results shows that both *DPSO* algorithms achieve better result than other algorithms. The swarm algorithms were tested with and without the ellipse detection module. The ellipse detection module appears to be superior to results with only the *DPSO* algorithms.

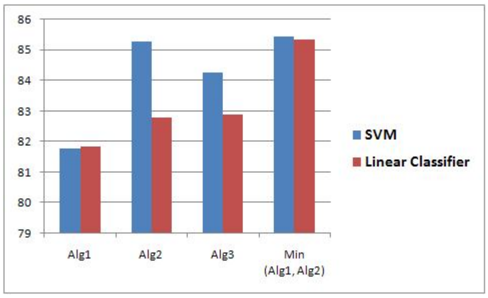


Figure 5. Algorithm comparison
The results of comparing the algorithms. The graphs displays the recognition rate of symbols.

The second experiment we implemented is testing the effect of symbol complexity and type on the recognition rate. Figure 6 shows the accuracy of each symbol, it is clearly noted that symbols that have only line segments achieve higher accuracy rate than other symbols. Figure 6 also indicates that algorithm *AlgS1* alone achieve better performance than algorithm *AlgS2* in the symbols that consist only of lines. This is natural as algorithm *AlgS1* divides strokes into line segments only but *AlgS2* is able to divide strokes into lines and curves based on the minimum error of the segment itself. Algorithm *Alg3* gives good performance as long as the symbols consist of lines and curves, if the stroke consists of curve only the algorithm may lead to wrong segmentation result. This is because the system divides the stroke first to line segments then tries to decide if each segment can be represent better as a curve unlike algorithm *AlgS2* where the curve segments are tested while choosing the best segmentation. Combining both algorithm *AlgS1* and *AlgS2* improved the recognition rate of all symbols because of combining the advantages of both algorithms. The penalty for this increased performance is in the computational time needed to run both the swarm algorithms.

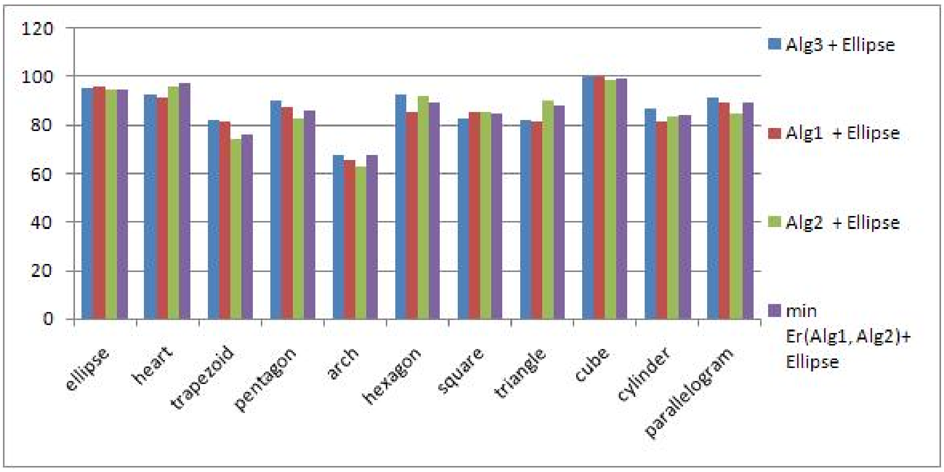


Figure 6. Symbols Comparison

The graph shows the recognition rate of each symbol using different algorithms.

6. Conclusion and Future Work

This paper presented a new approach to sketch recognition using PSO. The system uses both speed and curvature data which helps in improving the *DPSO* algorithms over the original algorithms [Chen *et al.*, 2003; Yin, 2004]. It is noted that the *DPSO*in general generates an optimized stroke segmentation which improves the final recognition rate. The tradeoff between accuracy achieved and time complexity must be further investigated to achieve better results. The use of statistical moments and structural features improves the recognition rate. The system was tested on 13 different symbols and achieved satisfying results. The system dose not depends on low level recognizer but rather on a set of high level features. This makes the system easily expandable with aspect to symbols recognized.

A possible extension of this research is to complete the clustering algorithm for fully automated sketch recognition. The clustering must be performed without the user explicit involvement. Other area of enhancements is the features extraction methods. Introducing more spatial and geometrical features is believed to improve classifications.

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