Sketch 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 Support Vector Machines(SVM) classifier which further improves the final recognition accuracy.

1. Introduction

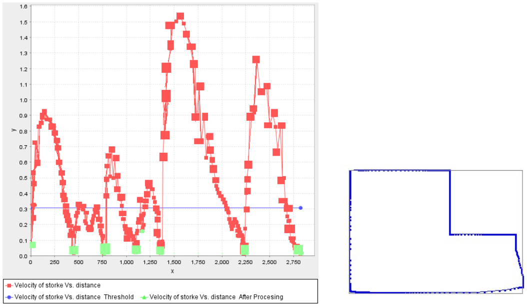
Scientists generally and engineers specifically express thoughts and designs using sketches. Engineers use sketches to exchange designs as a natural method of communication rather than writing or speaking. Design engineers need a powerful computer based system with symbol recognition to help them design, 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 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 4 shows that the proposed system improves the final symbol recognition accuracy.

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 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 [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.

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.



(a) The Speed of data (b) Stroke Sample

Figure 1. Data Curves
An example of the stroke drawn in the system with the curve that shows the speed of the points in the stroke.

3. System Details

The following sketch recognitions systems is divided into three main system blocks are 1) preprocessing, 2) segmentation and 3) Recognition. The following sections provides a detail description of each step.

3.1. Preprocessing

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

Figure 1(a) shows the computed speed data for the stroke drawn in Fig. 1(b). It is noted that the dominant points are characterized by lower speed values and higher curvature and direction values(Fig. 1(a)). After the system computes all the speed, time difference and curvature data it proceeds to detect the points with low velocity and high curvatures. The system adopted the *average thresholding* process presented by [Sezgin *et al.*, 2001]. This process is used to curvature, time difference and speed curves to generate a set of possible dominate pointsP_{pd}. These points are saved into a single array to be used as input to guide the next segmentation phase.

3.2. Segmentation

After computing the primary data the system tries to segment the stroke into a set of primitives. The segmentation algorithm first attempts to fit the stroke points into a curve or an ellipse uisng a minimum square error fitting algorithm. If the stroke proved to be an ellipse arc 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. **??**). The next section describes the two particle swarm algorithms used to divide the stroke.

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

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 $P_i = \{p_{ij} \,|\, j = 1, 2 \cdots N\}$ where p_{ij} has only two values 0 or 1. When $p_{ij} = 1$ means that point j is a dominant point.

The fitness functions 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 1

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

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 2

$$\max fitness(p_i) = \begin{cases} -E/\varepsilon N & if E > \varepsilon, \\ D/\sum_{j=1}^{N} p_{ij} & otherwise \end{cases} \quad (2)$$

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 3

$$E = \sum_{i=0}^{M} e(D_i) \quad (3)$$

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 4

$$\max fitness(P_i) = \frac{1}{E \times M^k} \quad (4)$$

where E is the error and M is the number of segments and k is a parameter tweaked to get minimum number of segments. 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 3.1), if it is not labeled the point is moved to the nearest labeled point. After that the particles are tested to make sure 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. 1 & 3 one of the points are either removed or moved to the nearest possible dominate point.

3.3. Recognition

After the user draws all strokes of the symbol, 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, 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).

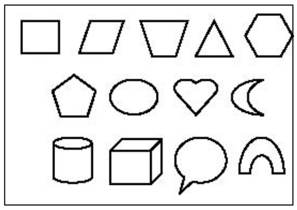
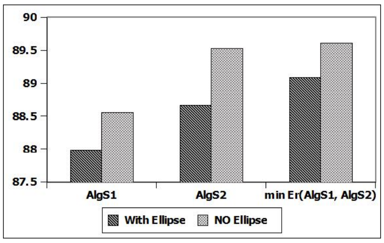


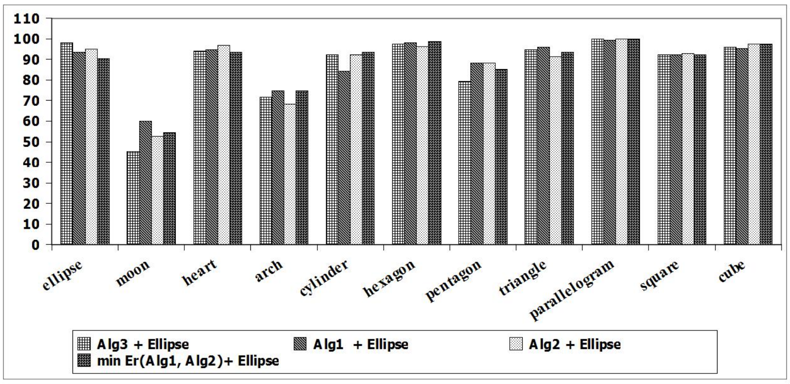
Figure 2. The Symbol Set
Ths figure shows a set of the symbols used in the dataset.

4. 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 2 shows a set of the shapes used in the data set. We divide the dataset into four sets each set contains four different users. Then 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*). Figure 3(a) 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 fitting module. The ellipse detection module appears to be superior to results with only the *DPSO* algorithms. The second experiment we implemented is testing the effect of symbol complexity and type on the recognition rate. Figure 3(b) shows the accuracy of each symbol, it is clearly noted that symbols that have only line segments achieve higher accuracy rate than other symbols.



(a) Algorithm comparison



(b) Symbols Comparison

Figure 3. Experiments results:
a)The results of comparing the algorithms. The graphs displays the recognition rate of symbols. b) The graph shows the recognition rate of each symbol using different algorithms.

Figure 3(b) 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. 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.

5. 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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