AUTOMATED TUNING OF PARAMETERS FOR THE SEGMENTATION OF FREEHAND SKETCHES

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Abstract: One of the main problems in the segmentation of freehand sketches is the difficulty of tuning the parameters involved in the process. Commonly, these parameters are chosen empirically from the observation of segmentation results in training sets. However, this approach rarely gets the best set of parameters, especially when the parameters depend on each other. This work presents an optimization algorithm, based on the simulated annealing technique, which tunes the segmentation parameters to improve segmentation results. The tuning of parameters has been formulated as an optimization problem where the cost function is expressed as the number of errors in the segmentation of a training set. Errors are determined comparing the computer segmentation with the correct one defined during the design of the shapes of the training set. Experimental work used 177 samples of 20 different shapes, achieving a performance ratio of 97.0% for the correct segmentation after tuning of parameters.

1 INTRODUCTION

Sketching is a useful tool which plays an important role in the new product development process. Different types of sketches are used in that process. Prescriptive or analytical sketches (Varley & Company, 2008) are hand-made technical drawings which contain detailed information describing a final design. They contain a full set of views complemented by symbolic information conveyed through standardized symbols, but they do not need to be geometrically perfect.

Computer processing of this kind of sketches and its integration on computer aided design applications still present many issues to be solved. With this aim, some research groups are exploring new paradigms for sketch analysis and understanding like agent-based architectures (p.e. Juchmes, Leclercq & Azar, 2005; Azar, Couvreury, Delfosse, Jaspartz & Boulanger, 2006; Casella, Deufemia, Mascardi, Costagliola & Martelli, 2008; Fernández-Pacheco, Aleixos, Conesa & Contero, 2009; Flasinski, Jurek & Myslinski, 2009; Fernández-Pacheco, Conesa, Aleixos, Company & Contero, 2009). In this context, our research group is performing the recognition process through a two level agent architecture, where "primitive agents" are in charge of the syntactic recognition, and "combined agents" carry out the semantic recognition using contextual information.

The reliability of primitive agents strongly depends on the robustness of the employed segmentation algorithm and its parameterization. So, one of the main problems in the segmentation of freehand sketches is the difficulty of tuning the parameters involved in the process. The way of drawing is different for each user and even if the sketched figures are quite similar, the segmentation can vary. Commonly, the initial or default values of the parameters to control the segmentation are chosen empirically from previous experience, but this rarely gets the best set of parameters, especially when the parameters are interrelated. These misclassifications are usually due to the difficulty of tuning the whole set of parameters altogether. In order to overcome this limitation this paper proposes an optimization approach using a simulated annealing (SA) algorithm (Kirkpatrick, Gelatt & Vecchi, 1983) to tune the segmentation parameters. There are some examples of application of

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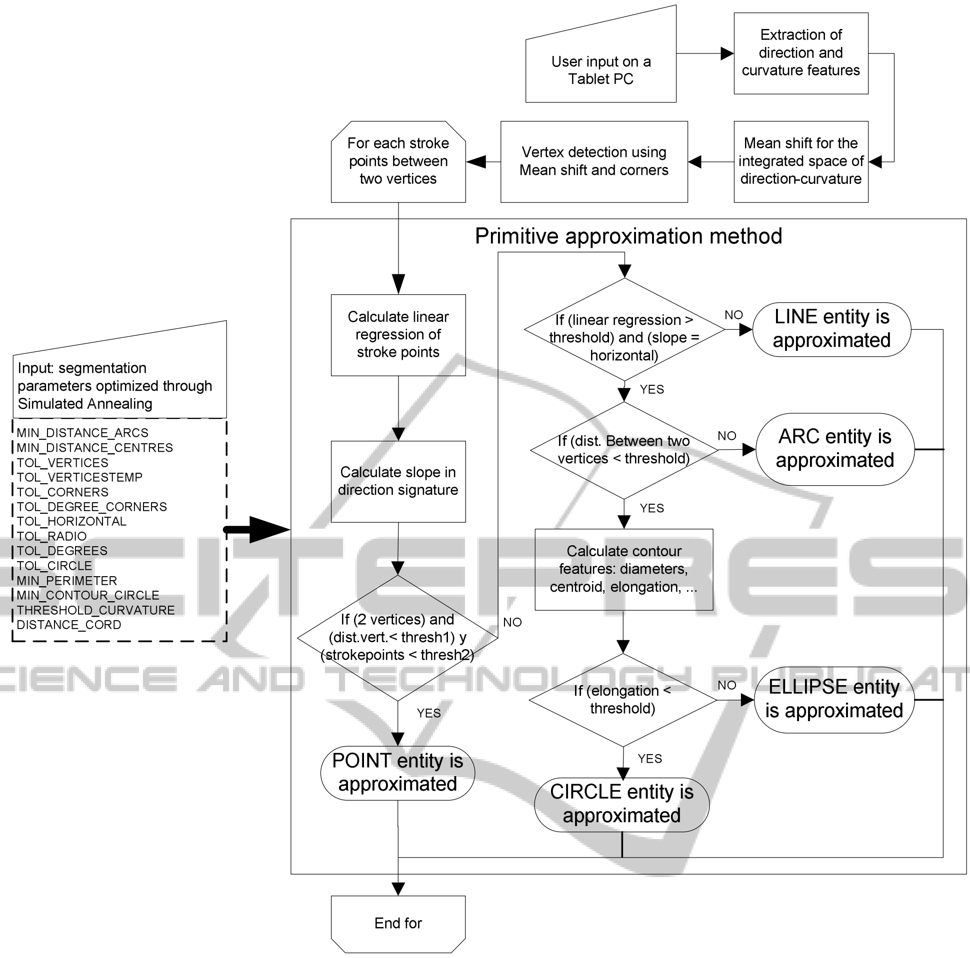


Figure 1: Flow chart of the segmentation algorithm (segmentation parameters listed in Table 1).

optimization algorithms to computer vision problems: Taylor and Wolf (2004) applied an optimization approach to improve the settings of their text detection algorithm in images and video sequences. Mbogho and Scarlatos (2007) used a genetic algorithm to tune the colour thresholds to minimize the effects of lighting variations on the recognition of colored visual tags. Gelasca, Salvador and Ebrahimi (2003) proposed a framework for an intuitive tuning of parameters in image and video segmentation algorithms. Other applications to processes related to computer vision have been developed by Mukerjee et al. (1997), Davis et al. (2008), or Iakovidis et al. (2007).

The article is organized in the following way: first the segmentation process is explained (including the sketch correction, the vertices detection procedure and the primitive approximation method), secondly the implementation of the optimization process by means of the simulated annealing algorithm is detailed, and finally, experimental work and results are given.

2 THE SEGMENTATION ALGORITHM

Our application SegSGeo (Segmenting Sketched Geometry) analyzes a stroke when a pen up event is encountered, and fits the sketch into an outlined sketch (poly-line). Its structure is shown in figure 1 and the procedure consists of five steps:

1. Direction and curvature signatures of the stroke are calculated.
2. The mean shift (smoothing technique) procedure is applied to the two previous signatures (Yu, 2003).
3. Changes in direction of strokes are detected, and vertices are fixed using peaks in smoothed curvature signature.

4. A refinement of vertices is carried out when their path length is less than a desired threshold fixed empirically.
5. Finally, the type of each entity between a pair of vertices is decided by means of a primitive approximation method. Supported entities are lines, arcs, circles and ellipses, and its type is decided by looking into the direction signature before Mean shift is applied, and analyzing the points corresponding to that piece of the stroke.

2.1 Extraction of Direction and Curvature Signatures

The stroke is composed by a set of coordinates (x,y) in an interval of pen-down and pen-up events. In such a stroke, there are two visual features which can guide recognition: direction and curvature. The direction gives the angles between two consecutive pairs of coordinates in the range [-π,π]. The curvature gives the arctangent of the direction between two consecutive points, to inform on how opened or closed such piece of the stroke is.

2.2 Finding Vertices

Mean shift procedure (1) has been used to smooth the collected stroke, since it has proven to give good results in analyzing clusters in feature space, and in eliminating noise (Yu, 2003).

$$z_{j+1} = \frac{\sum_{i=1}^{n} x_i k'\left(\left\| \frac{z_j - x_i}{h} \right\|^2\right)}{\sum_{i=1}^{n} k'\left(\left\| \frac{z_j - x_i}{h} \right\|^2\right)}, j = 1,2,... \qquad (1)$$

In order to apply this procedure to the two-dimensional direction-curvature joint space, we will consider x_i, $i=1,2...n$ (where n is the number of points in the direction-curvature joint space) as the input vector of the mean shift procedure, that is, the joint space d_i and c_i; and z_i as the output vector of smoothed discrete values of direction and curvature, that is, the new direction and curvature signatures after smoothing. The term *k'* is the derivative of the profile of Gaussian kernel $k(x) = exp(-x / 2)$, and the term h is the "bandwidth", that is, the smoothing parameter, which has been adjusted to h_d and h_c, depending on direction and curvature respectively.

The smoothed curvature signature guides us to find vertices in the stroke when seeking for local maxima values, that is, where curvature changes considerably (peaks in curvature signature figure 2c). The vertices seek routine finishes merging two consecutive vertices when the path length between them is lower than a threshold.

In the example of figure 2, six vertices are found, and the first entity is approximated to an arc (arc through 3 points: initial, final and middle of the first section of the stroke) and the rest of entities to lines. This has been achieved looking into both, the original direction signature before mean shift procedure between each two consecutive vertices, and the correlation with the linear regression of the stroke points of each entity, what is done by means of the primitive approximation method.

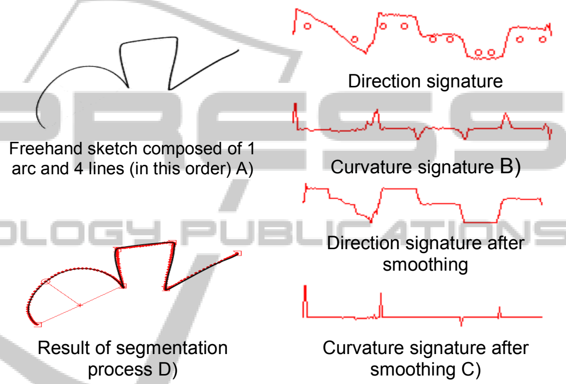


Figure 2: Example of a sketched figure.

2.3 Primitive Approximation Method and Segmentation Parameters

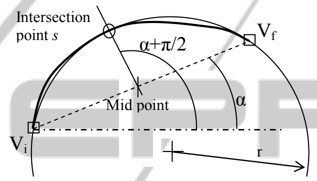
The original direction signature and the correlation of the stroke points from their linear regression are used to identify the primitive entities composing a stroke. If the features of the corresponding stroke points are analyzed and the direction signature is found to be horizontal, then that section of the stroke is approximated to a line; otherwise it can be approximated to an arc, circle or ellipse (see Figure 3). To approximate the section to an arc entity, the direction signature must be inclined and the vertex ends V_i and V_f separated, thus the section is fitted to an arc by three points V_i, V_f and s. If the vertices are close, the section is approximated to a circle or ellipse depending on the elongation (quotient between major R and minor r radius).

The segmentation process is controlled by 14 parameters, listed in Table 1. For each parameter a range of values from previous observations has been established (range column).

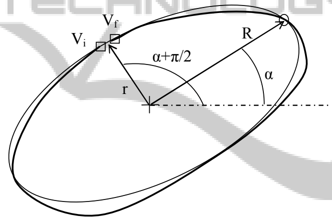
Table 1: Parameters of the segmentation and its initial range.

Parameter	Description	Range
MIN_DISTANCE_ARCS	Distance between the two ends of an arc	[0,50]
MIN_DISTANCE_CENTRES*	Distance between the centers of two consecutive arcs	[0,100]
TOL_VERTICES	Tolerance for the distance between two consecutive vertices	[0,30]
TOL_VERTICESTEMP	Involved in the seek for local maximums and minimums	[1,30]
TOL_CORNERS	Distance from a point to both sides to calculate the angle of a corner	[1,20]
TOL_DEGREE_CORNERS	Threshold to considerate a corner as a vertex	[1,60]
TOL_HORIZONTAL	Tolerance for a horizontal slope	[0,0.05]
TOL_RADIO*	Tolerance for large values of radio	[200,600]
TOL_DEGREES*	Tolerance for the orientation of two consecutive lines	[0º,30º]
TOL_CIRCLE	Tolerance for the quotient of diameters to distinguish a circle from ellipse	[0.3,0.8]
MIN_PERIMETER	Minimum length for a line or arc	[2,10]
MIN_CONTOUR_CIRCLE	Minimum contour for circle or ellipse	[30,200]
THRESHOLD_CURVATURE	Tolerance for vertices in order to consider the stroke a circle or ellipse	[0.1,0.5]
DISTANCE_CORD	Arc length to help the decision of an arc or a line	[20,300]

* Refinement parameters.



a) Fitting a stretch of sketch to an arc.



b) Fitting a stretch of sketch to a circle/ellipse.

Figure 3: Parameters calculated for arcs/circles/ellipses entities.

3 TUNING OF SEGMENTATION PARAMETERS

The steps for tuning the parameters of the segmentation process consist of four main parts:

1. Definition of the initial range of values for each segmentation parameter based on previous experience.
2. Automatic tuning of parameters inside their initial range using a simulated annealing algorithm.
3. Definition of the definitive range of values for each segmentation parameter, analyzing the behaviour of each parameter when the rest of parameters are fixed to their optimal values.
4. Automatic tuning of parameters inside their definitive range using a simulated annealing algorithm.

The quality of the obtained segmentation is evaluated by means of a cost function (2) that returns a real value (cost) from a set of n segmentation parameters $P = \{p_1, p_2, \dots p_n\}$.

$$c : P \rightarrow \Re \qquad (2)$$

The cost value for a set of parameters is defined as the ratio of bad segmented shapes using this set of parameters. A library of sketched figures and their correct segmentation has been developed in order to implement the cost function (examples at Figure 4).

The correct or ideal segmentation has been previously defined by consensus by the research team of this work. The criteria applied to define a well segmented shape are based on an all-or-nothing accuracy, that is, a shape is well segmented if:

- The number of vertices must match the ideal segmentation.

- The type of fitted primitives connecting the vertices must match the intended primitives of ideal segmentation.

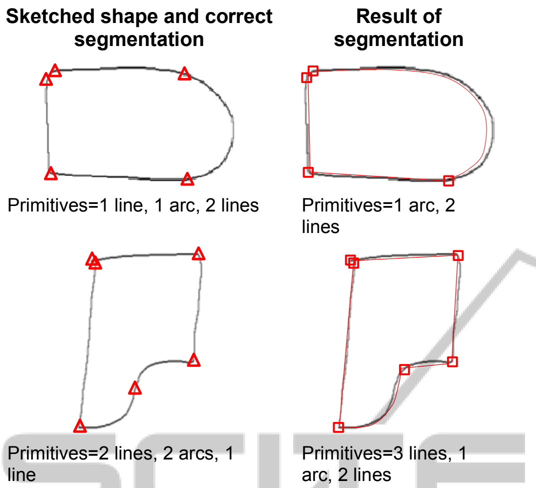


Figure 4: Examples of missegmentations. (Intended segmentation vertex (△), recognized vertex (□) and recognized primitive in red color).

3.1 Tuning of Parameters using a Simulated Annealing Algorithm

The next step carried out to determine the optimal range of the segmentation parameters is implemented by a simulated annealing algorithm (Kirkpatrick, Gelatt and Vecchi, 1983). The SA algorithm is shown in figure 5 and described below. The parameters involved in the SA algorithm can be classified as generic or specific.

The “generic parameters” or "annealing schedule" control the operation of the algorithm. They are:

- *Initial Temperature*: initial value of temperature at the beginning of the SA process. It is calculated using the following expression (Kouvelis et al., 1992):

$$T_0 = \frac{\overline{\Delta C^{(+)}}}{\ln\left(\chi_0^{-1}\right)} \tag{3}$$

where $\overline{\Delta C^{(+)}}$ is the mean value of the cost increment associated to those displacements with an increment in the cost function. In our particular case, the tests performed show that for 100 displacements, $\overline{\Delta C^{(+)}} \approx 1.5$. Where χ_0 is the expected initial coefficient of acceptance (χ is the rate of accepted displacements with respect to the total number of attempts). Using a typical value of this coefficient in the literature (χ_0=0.75), the resulting value for initial temperature is $T_0 \approx 5$.

- *Cooling Schedule:* indicates how temperature varies from two different steps. The more common form consists of a potential cooling (faster with high temperatures):

$$T_{m+1} = k \cdot T_m \tag{4}$$

where m is the current temperature step, and k is the cooling coefficient. A rapid cooling (small values of k) causes a quick fall in the cost, but if it is too fast, the SA may exit without reaching good solutions. Moreover, a slow cooling down makes the cost function to have ups and downs (high cost displacement are allowed) but increases the number of iterations (the time required) and the probability of finding the optimal solution. A value of 0.5 has shown a good compromise with respect to cost and speed.

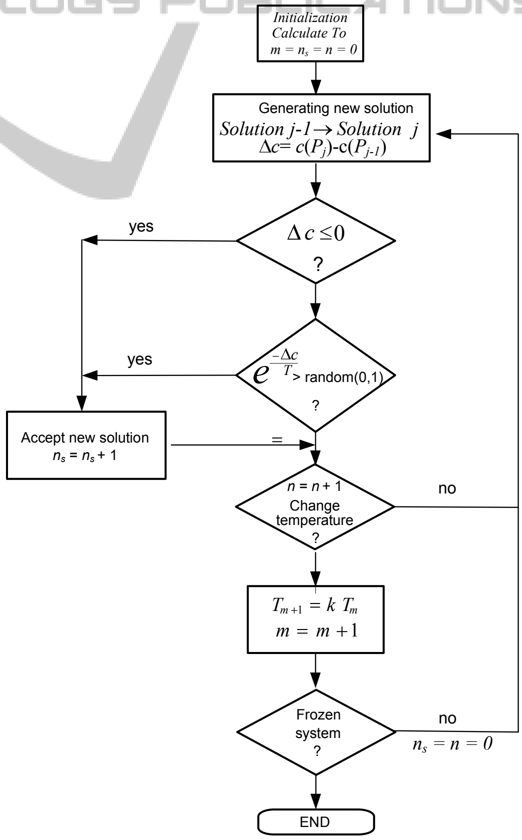


Figure 5: SA algorithm.

- *Balance Criterion (change temperature):* it decides when the temperature must go downhill to the next step using this logical condition:

$$\left(n_s > n_s^{\max}\right) OR \left(n > n^{\max}\right) \quad (5)$$

Where:

- n_s is the number of successful displacements in the present temperature step.
- n_s^{max} is the maximum number of successful displacements in a temperature step. Usually this number is determined according to the size of the space of solutions. In this problem, the used value is the number of parameters to optimize, in this case with 14 parameters, $n_s^{max}=14$.
- n is the number of attempted displacements in the present temperature step.
- n^{max} is the maximum number of attempted displacements in a temperature step, and usually is proportional to the n_s^{max} value. In the current context, $n^{max} = 2\cdot n_s^{max}$, so $n^{max} = 28$.

▪ *Freezing Criterion:* it is the stop criterion that terminates the SA process:

$$\left(\chi < \chi_{\min}\right) OR \left(m > m^{\max}\right) \quad (6)$$

The freezing condition can be accomplished when the temperature has experimented a specific number of downhill moves (m^{max}), or when the coefficient of acceptance is very low ($\chi = n_s / n$), where:

- χ_{min} is the minimum coefficient of acceptance, in this case 1% is the selected value.
- m^{max} is the maximum allowed number of temperature steps, in this case the selected value is 50.

The specific parameters of the SA in the context of our problem are:

▪ *The Space of Solutions P,* that in this case corresponds to the 14 parameters used for segmentation (see table 1):

$$P = \{p_1, p_2, \dots p_{14}\} \quad (7)$$

▪ *A displacement mechanism for choosing a solution nearby the current one.* For each parameter pi to optimize in the iteration j, its value is obtained from its previous value (from the iteration j-1) as follows:

$$p_{ij} = p_{i(j-1)} + \delta_i \cdot \xi_{ij} \quad (8)$$

Where $p_i \in [p_i^{min}, p_i^{max}]$, $\delta_i=\alpha\cdot(p_i^{max}- p_i^{min})$, and α is the maximum displacement ratio (α = 0.1 provided a good performance in the current problem). ξ_{ij} is a random number in the range $[-1,1]$, obtained for each parameter in each iteration.

▪ *The cost function* $c : P \rightarrow \Re$ that gives a value that must be minimized. For a training set of nt sketched figures this function is defined as:

$$c = n_m / n_t \quad (9)$$

Where n_m is the number of mistakes corresponding to those bad segmented shapes applying the criterion defined at the beginning of section 3.

The best solution obtained during the optimization process is stored, in order to avoid situations where the final solution does not correspond to the optimal one.

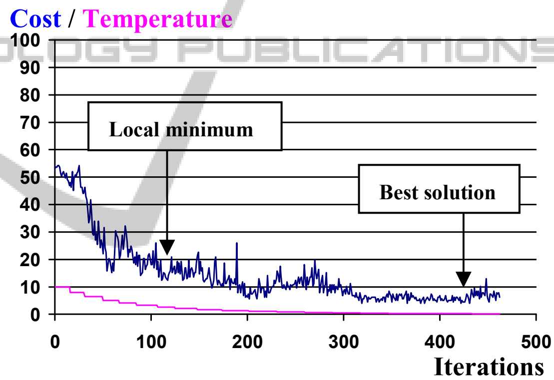


Figure 6: Cost and temperature evolution in a SA process.

3.2 Individual Parameter Adjustment

After the first simulated annealing step, in order to establish the definitive range for a specific parameter p_i we have fixed the rest of the parameters to their optimal value (obtained from the previous simulated annealing step), and the cost is obtained with the parameter p_i ranged in its whole initial range (and expanded if it is necessary). The definitive range is fixed centring it in the optimal value obtained from the process and expanded or compressed if it is necessary.

Figure 7 shows the initial or default range for the segmentation parameter TOL_VERTICES fixed from expertise. As notice, the value of this parameter for the minor cost function is beyond the right value 30, so best results in segmentation are never reached. Figure 8 shows the corrected range for this parameter. Now, the optimal value is centered in the range so better results in segmentation can be achieved.

So, the value of the parameter for the lowest function cost has been centered in a range, and its width has been fixed in order to avoid the function cost increase more than a percentage. This width is variable for each parameter.

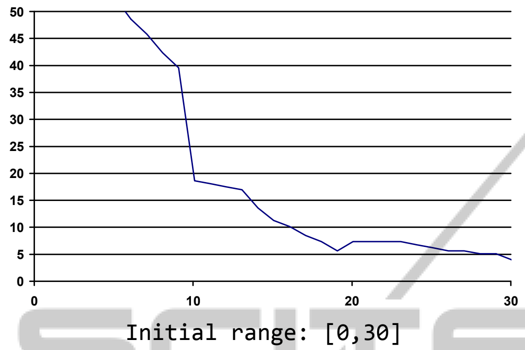


Figure 7: Initial range for parameter TOL_VERTICES.

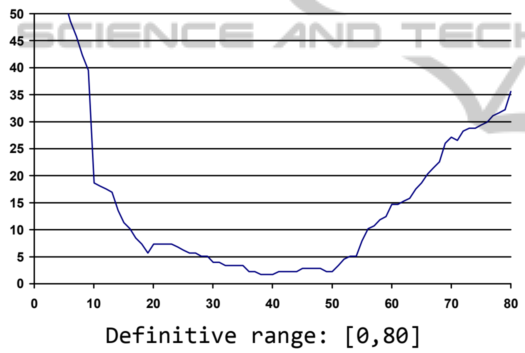


Figure 8: Definitive range for parameter TOL_VERTICES after the correction process.

When all the ranges have been adjusted, the second simulated annealing step provides the final segmentation parameter values.

4 EXPERIMENTAL WORK

The segmentation process has been applied to a set of 177 samples of 20 different sketched figures (including circle and ellipse) collected from 3 users and stored in a DB. Each user drew 3 samples of each figure, and 3 figures with poor quality were discarded.

Figures 9 and 10 show some examples of sketched figures segmented using the parameters optimized with the SA algorithm.

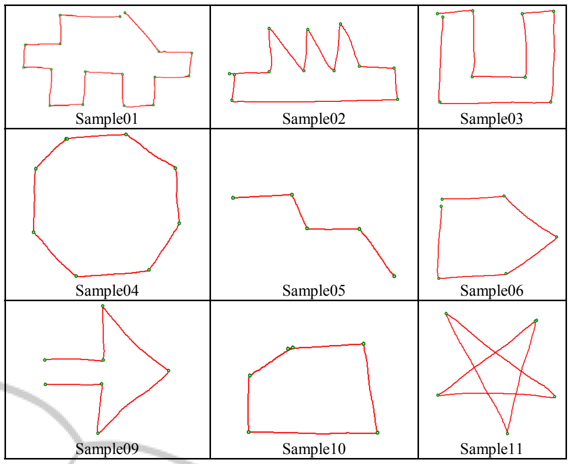


Figure 9: Examples of sketched figures used in the tests including only lines.

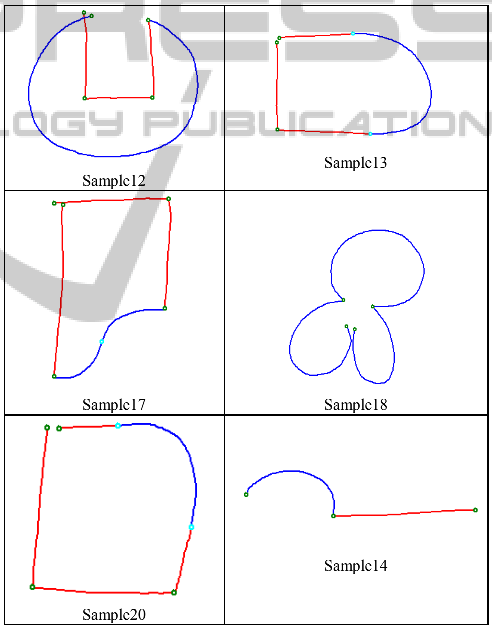


Figure 10: Examples of sketched figures used in the tests including lines (in red) and arcs (in blue).

The segmentation process has been carried out with a different set of segmentation parameters for each SA iteration. And the SA process has been made up with different ranges for segmentation parameters and different values for SA parameters as described in section 3.

5 CONCLUSIONS

From results obtained, we can state that the optimization process improves significantly the results of the segmentation, demonstrating that, in general, the recognition process can benefit much if optimization techniques are applied to its parameters tuning them for their optimal values. The results improved in more than 10% respect those obtained with previous parameters fixed empirically from observation. The segmentation approach SegSGeo with the optimization process obtained a success of a 92% of well segmented figures (all-or-nothing-accuracy), which increases to 97% if we consider isolated entities instead of complete figures.

With respect to the optimization technique, tests with different SA parameters show a very stable behavior of SA algorithm, so it can find good solutions though the SA parameters vary within a fairly wide range. The most critical parameter is the displacement mechanism, that is, the maximum displacement ratio α: it must be high enough to get out from local minimum, but not too high to avoid jumping haphazardly (see figure 11).

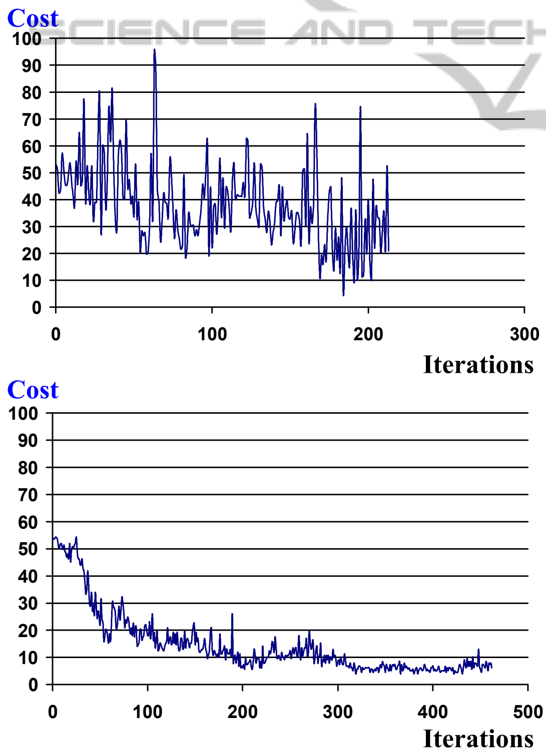


Figure 11: Cost evolution in two different SA processes (above: α=0.4) (below: α=0.1).

The following parameters in order of importance are those that control the cooling scheme: the initial temperature T_0 and cooling coefficient k. The probability of finding an optimal solution increases when more tests are performed with a slow cooling (higher T_0, or k closest to 1), but increasing the time too. Good solutions can be found with a set of SA process with a fast cooling scheme or with a single SA process with a slow cooling scheme.

Tests show that classical values for balance and freezing criterions (dependent on the number of parameters to optimize) are appropriate. On the one hand, changes in balance criterion have a similar effect that changes in cooling scheme, on the other hand, changes on freezing criterion do not significantly affect the SA time or result.

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