Polygonal Approximation of an Object Contour by Detecting Edge Dominant Corners using Iterative Corner Suppression

Rabih Al Nachar[1], Elie Inaty[1], Patrick J. Bonnin[2] and Yasser Alayli[2]
[1]*Department of Computer Engineering, University of Balamand, PO Box 100, Elkoura, Lebanon*
[2]*Laboratoire d'Ingénierie des Systèmes de Versailles-LISV, 10-12 Av de l'Europe, 78140 Vélizy, France*

Keywords: Straight Edges, Corners, Polygonal Approximation, Contour.

Abstract: A new algorithm to detect straight edge parts which form the contour of an object presented in an image is discussed in this paper. This algorithm is very robust and can detect true straight edges even when their pixel's locations are not straight due to natural noise at the object borders. These straight edges are than used to report and classify contour's corners according to their angle and their adjacent segments lengths. A new technique for polygonal approximation is also presented to find the best set among these corners to construct the polygon vertices that best describe the approximating contour. It starts by eliminating the corners, one after the other using Iterative Corner Suppression (ICS) process. This in turn enables us to obtain the smallest possible error in the approximation. Experimental results demonstrate the efficiency of this technique in comparison with recently proposed algorithms.

1 INTRODUCTION

The problem of straight edge detection can be defined as follows: Given a binary image of edges extracted from a real image using an existing edge detector based on Sobel, Prewitt, Kirsh or Canny algorithms (Prewitt 1979, Sobel 1978, Kirsh 1971 and Deriche 1987), find the parts of an edge that can be classified as straight edges or segments of length greater than a given threshold. The importance of developing an algorithm that can detect these straight edges remains a very important task in computer vision and pattern recognition (Loncaric 1998). In addition, straight edges are encountered a lot in human made internal and external urban environments and objects. For example, Herman in (Herman, Kanade and Kuroe 1984) presents an application for an aerial robot to form and update of a 3D map of a sequence of aerial scenes. The dedicated objects to be detected in these images are the buildings. So he identified them by their straight edges and their intersection at the corners. Other applications are indoor applications where a robot tries to build a map of its environment and localize itself in it which is called the SLAM problem. The target objects, used for this purpose, are identified by their straight edges like doors and walls intersection. In other application, a combination of straight edges is used (Bouchafa and Zavidovique 2006) to form specific shapes like V-shape, W-shape and Z-shape. Each shape is invariant under a specific image transformation. For this reason, it is used for image registration.

The most important objective of extracting straight edges is their role in identifying corners that are used as interest points in a lot of algorithms in image processing. A corner (Nachar, Inaty, Bonnin and Alayli 2012) can be defined as intersection of non collinear straight edges with appropriate length. From here, correct detection of straight edges will lead to efficient corners detection.

After extracting the image corners based on straight edges of a shape, we have developed a new technique for "polygonal approximation" that consists of selecting a number of well chosen corners to construct the polygon that best approximates the contour of that shape. Polygonal approximation is widely used in object recognition (Ayache and Faugeras 1986) because it smoothes the contour of the objects in the images without loss of critical information. Related works to this algorithm are cited in the next section.

The rest of the paper is organized as follows: Section 2 presents some related works on polygonal approximation. Section 3 describes the edge extraction and the chain code of every edge point. Section

Al Nachar R., Inaty E., J. Bonnin P. and Alayli Y..
Polygonal Approximation of an Object Contour by Detecting Edge Dominant Corners using Iterative Corner Suppression.
DOI: 10.5220/0004650602470256
In *Proceedings of the 9th International Conference on Computer Vision Theory and Applications* (VISAPP-2014), pages 247-256
ISBN: 978-989-758-003-1

4 explains our proposed algorithm using polygonal approximation. Experimental results are revealed in Section 5. The conclusion is shown in Section 6.

2 RELATED WORKS

A large number of methods were proposed so far (Dunham 1986). Pavlidis in (Pavlidis 1982) presents an algorithm, known as split and merge technique. It divides an edge into a set of segments that has each one a maximal distance to the edge less than a given threshold d as shown in Figure 1.

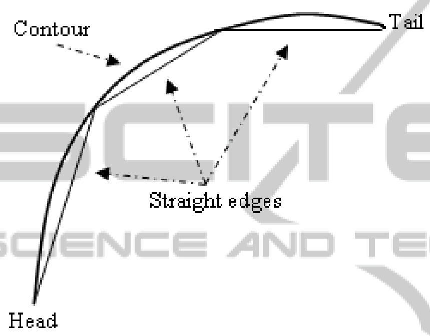


Figure 1: Polygonal Approximation.

The parameter used in this technique is the maximal distance d_{max} between the segment and the edge as described in Figure 2. If d_{max} is greater than the threshold d, the segment [AB] is divided into two segments; [AM] and [MB] where M is the edge point corresponding to d_{max}.

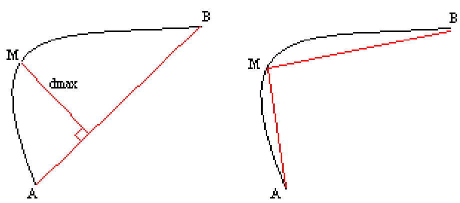


Figure 2: Segment division according to maximal distance.

Wall and Danielsson in (Wall and Danielsson 1984) presented another algorithm that tries to find the segment [AB] shown in Figure 2 by moving its end-point B starting from the edge point A along the edge until a certain criterion is no longer verified. The criterion used here is the maximal area per unit of length of the deviation between the edge and the corresponding approximated segment that should be less than a given threshold. Another technique for obtaining a polygonal approximation of an object's contour based on an updated Hough Transform is presented in (Gupta, Chaudhury and Parthasarathy 1992). On the other hand, the method in (Mikheev , Vincent and Faber 2001) is dedicated for the polyline representation of a scanned text or graphic objects. Kolesnikov in (Kolesnikov 2008, 2009, 2011) focused on the approximation of a polygonal edge or curve P of N vertices by another polygonal edge Q with a minimal number of segments or vertices M (M<N) while conserving a given criterion so that the resulting error does not exceed a given threshold. The error is the sum of the square distances of the N vertices of curve P relative to the curve Q. Pinheiro in (Pinheiro 2010) searched for edge points, called curvature extremes, that correspond to a change in the direction of the curve (edge) using a curvature function which form the polygon vertices. These extremes are selected at different scale level of the smoothed image. When the scale level increases, the edge details become smoother so the number of extremes will be reduced. Parverz and Mahmoud in (Parvez and Mahmoud 2010) searched for cut-points on the contour of the studied shape. These points correspond to a deviation in the contour direction. Then the algorithm tries to minimize the number of detected cut-points until a terminating condition is satisfied. The final approximated polygon will have these cut points as extremes.

In (Carmona-Poyato, Madrid-Cuevas , Medi-naCarnicer and Munoz-Salinas 2010), the authors presented a technique based on detecting dominant points on the contour and then iteratively suppressing the redundant ones in order to obtain the best approximated polygon with the minimal number of segments. The algorithm of Masood in (Masood 2008) also detects first dominant points called break points then starts to eliminate the ones with minimal error value based on global measure. The optimal result is not guaranteed even with the usage of an optimization procedure. Finally, Marji and Siy in (Marji and Siy 2004) presented a very similar technique to the one used in (Masood 2008) but it differs by the measure of error of each dominant point. Here, a dominant point is characterized especially by its strength that means its non collinearity with respect to its direct neighbors.

We have proposed in this paper an approach inspired by that presented in (Marji and Siy 2004 and Masood 2008). We have searched for dominant corners that best approximate a given shape by a polygon having these corners as vertices. The differences between our work and their works are in the nature and stability of the selected points and in the method used to select these points among others. On the other hand, the error measure used to eliminate or to keep a corner is based on the Integral Square Error between an edge part and the straight segment approximating it. So, it is similar to the criterion used by Wall and Danielson (Wall and Danielsson 1984) that relies on the area of the region included between the edge part and its approximated segment rather than only relying on the maximal distance like in the method of Pavlidis (Pavlidis 1982).

3 EDGE EXTRACTION AND CHAIN CODE

3.1 Edge Points Extraction

Given an original image, the extraction of edge points is performed in several steps:

- Gradient computation: in norm (magnitude of the edge) and direction (normal to the edge direction).
- Threshold on gradient norm, to extract initial edge points.
- Thinning edge points to thin thick edges to one pixel width.
- Prolongation of edge points to close open edges.
- Linking edge points to obtain edges (lists of hooked edge points) from edge points.

Three possibilities to obtain gradient computation, in norm and direction, which are:

1) Either Prewitt (Prewitt 1979) or Sobel Algorithm (Sobel 1978), which consist in two steps :
   - Compute the gradient projections on X and Y axis, using two masks : Gx and Gy,
   - then compute the norm and the direction using a rectangular to polar transform,
2) Kirsh algorithm (Kirsch 1971), which obtains directly the gradient in norm and direction, by choosing the best approximation among the four projections: horizontal, vertical, and two oblics using four masks: Gx, Gy and G+45 and G-45.
3) Canny edge detector (Canny 1986 and Deriche 1987) using the first derivative of a Gaussian function. The zero-crossing points are the edge points.

3.2 Edge Chain Codes

Linking an edge pixel C consists of identifying the direction of transfer from it to one of its eight neighbors, who has the greatest gradient norm. This direction is one of the eight Freeman directions coded in Figure 3.

3	2	1
4	C	0
5	6	7

Figure 3: Freeman Codes.

As a result, a linked edge can be viewed as a chain of Freeman codes of length equal to the number of linked edge pixels (edge length) minus one. As an example, Figure 4 shows a particular edge of nine pixels with its chain codes.

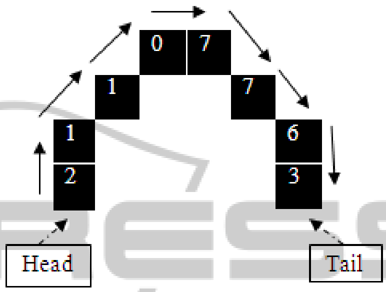


Figure 4: An edge with its chain codes.

4 POLYGONAL APPROXIMATION

The main goal of this paper is to introduce an operator that is able to extract a polygon that best approximate an object's contour. The operator's algorithm is composed of three functions that work sequentially as shown in Figure 5.

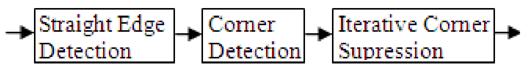


Figure 5: Algorithm's Block Diagram.

4.1 Straight Edge and Corner Detectors

Our objective is to detect edge parts that can be considered straight using only their chain codes. Then, the intersection edge points of every two non collinear edge parts are detected as corners. To do that, we must introduce the chain codes of straight edges.

4.1.1 Perfect Straight Edges

A perfect straight edge is an edge whose chain code is composed of one code or two codes at maximum. There are eight different straight edges corresponding to a unique code among the eight Freeman codes. For example, a perfect horizontal straight edge has a chain code of only 0 or 4 and a perfect straight edge along the first diagonal has a chain code of 1 or 5 as shown in Figure 6.

In addition to these eight cases, a perfect straight edge has a chain code composed of two codes: one primary and the other secondary with a difference equal to one between them. The classification of these two codes is done according to their frequency of occurrence in the edge's chain code. This is illustrated in Figure 7.

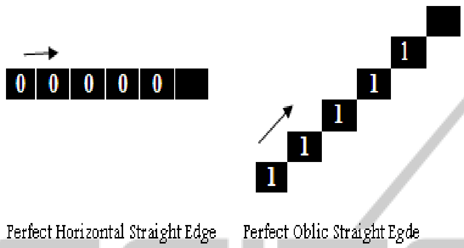


Figure 6: Straight Edges with unique code.

In Figure 7, five edges are considered starting from one origin O. Edges1 and edge5 are those that have a unique code 0 and 1 respectively, and their slope are 0^o and 45^o. Edge3 is the one that have double codes 0 and 1 of the same frequency of occurrence so its slope is 22.5^o and it is the bisector of the angle formed by edge1 and edge5. Edge2 is near to edge1 and has also double codes 0 and 1 but with different frequency of occurrence. Code 0 is primary and code 1 is secondary. Same result can be seen in edge4 that has code 1 as a primary and code 0 as secondary.

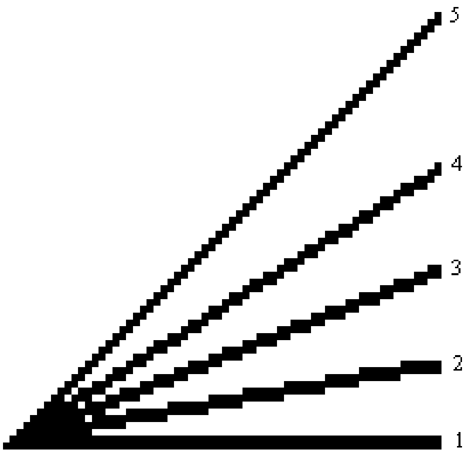


Figure 7: Straight edges with double Freeman codes.

As a conclusion, we can say that the perfect straight edges that have double codes are of two kinds. The first kind of edges has double codes of same frequency (edge3). It is equidistant between two straight edges of unique code (edge1 and edge5). The second kind of edges also has double codes but of different frequency (edges2 and4) and it is also between two straight edges of unique code corresponding to the primary or secondary code. Here, the nearest one's code forms the primary code. In Figure 7, Edge1 is the nearest to Edge2, so the primary code for Edge2 is 0.

4.1.2 Algorithm Explanation and Real Straight Edges

In real images, the chain code of a straight edge that should be composed of one or two successive codes has usually more than two codes. Our goal is to identify which of them are the primary and secondary codes and reject the remaining codes. This problem is due to natural noise at the object borders.

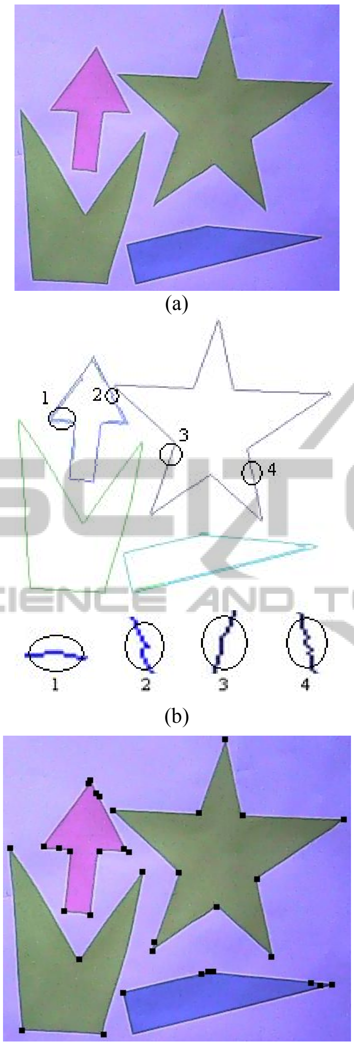
Real straight edges are shown in Figure 8 (a) where some perturbations, circled in the image of edges Figure 8 (b), are encountered along these edges. The challenge is to build an intelligent algorithm that can identify these perturbations and detect real straight edges that meet at corner points as shown with their angles in Figure 8 (c).

Our algorithm can be initiated at any edge point E. The purpose is to test the existence of a real straight edge with successive noisy pixels less than *m* and of a length greater than a threshold *d*. The idea behind the algorithm is to start testing an image edge starting from its head to its tail. Consider the first encountered edge direction as primary direction and the next encountered edge direction as secondary edge direction. While moving the current pixel to the tail, increment the frequency of primary or secondary directions when the current pixel's direction corresponds to primary or secondary directions, respectively. Or increment the frequency of noisy pixels, if the current pixel's direction differs from them. If the number of noisy pixels exceeds a given threshold *m*, the edge test stops at the current pixel. Now, if the edge length is greater than another threshold *d*, the edge traversed so far is considered as a straight edge.

Let us define the variables used in the algorithm:

- *pdir*: edge primary direction.
- *pdirfreq*: frequency of pdir.
- *sdir*: edge secondary direction.
- *sdirfreq*: frequency of sdir.
- *cdir*: current pixel direction.
- *InfectedCount*: number of noisy pixels en countered so far.
- *el*: edge length.
- *SecondaryFound*: a flag that is set when a second

ary direction is found.
- *diff*: absolute difference between cdir and pdir



(a)
(b)
(c)

Figure 8: (a) Real image, (b) image of edges, (c) detected corners.

The algorithm details can be listed as follows:

- *Record the first edge direction at E (Freeman code) as pdir and initialize pdirfreq* = 1. *Initialize InfectedCount* = 0, *el*=1 *and SecondaryFound = false and proceed to the next linked pixel.*
- *Iterate until the current pixel C reaches the tail of the edge.*
  - *Calculate diff .*
  - *If (Not SecondaryFound):*
    - *if (diff==*1*), record cdir as sdir, initialize sdirfreq* = 1 *and put SecondaryFound = true.*
    - *else if (cdir==pdir) than increment pdirfreq.*
    - *else increment InfectedCount.*
  - *Else*
    - *If(diff>=*2*)or((diff==*1*)and(cdir!=sdir))current pixel is a noisy pixel than increment InfectedCount.*
      - *if (InfectedCount>m): meaning that we are reached the maximum allowable noisy pixels: stopping criterion=>Ends of straight edge test:*
        - *if(el>=d) than the current edge is a real straight edge.*
    - *else if (cdir==pdir) than increment pdirfreq and set InfectedCount=*0*.*
    - *else if (cdir ==sdir) than increment sdirfreq.*
    - *update pdir and sdir: pdir is the direction that has the maximum frequency between (pdir, pdirfreq) and (sdir, sdirfreq).*
  - *el++.*

A noisy pixel is an edge pixel, located on a real straight edge, whose edge direction is different than those of the corresponding perfect edge. From here, the variable *diff* is introduced. Next, the search is for the edge direction, if exists, that differs by one from the primary direction *pdir* knowing that a perfect straight edge can have a chain code composed at maximum of two codes with difference equal to one. The variable *InfectedCount* is incremented each time a noisy pixel in encountered and it is cleared only if the current edge pixel direction *cdir* is equal to *pdir*. On the other hand, if *cdir* is equal to *sdir*, the variable *InfectedCount* should not be cleared. In Figure 9 (a), consider the example of a straight edge whose pixels are in black. It is linked with *pdir* = 1 and *sdir* = 2. At point A, the *cdir* is 3 so *InfectedCount* is incremented. Next at point B, the *cdir* is 2 and it is clear that the remaining edge in gray forms a different straight edge. If we reset *InfectedCount* at B when *cdir* = *sdir* = 2, the algorithm will not stop and will consider both edges, in black and in gray, as one straight edge which is incorrect. A final point should be discussed which is the need to update *pdir* and *sdir*. The logical reason for this case is that a straight edge primary direction is not necessary the first encountered *cdir* as shown on the straight edge in Figure 9 (b). Initially *pdir* = 4 and *sdir* = 5. But after traversing the remaining edge pixels, it is clear that *pdir* should be 5 and *sdir* should be 4.

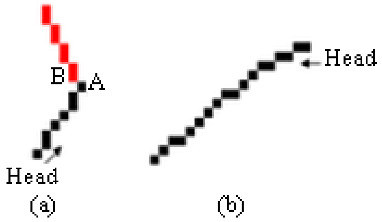


Figure 9: Two straight edges.

Finally, after the detection of straight edges the corner detection process starts by considering the intersection points of every two non collinear straight edges as corners.

4.2 Polygonal Approximation using Iterative Corner Suppression

In this section, we develop a novel technique based on corner points called Iterative Corner Suppression (ICS). Here, the corners, reported by the corner detector, are characterized by the lengths of its two sides (straight edges) and by its angle between its two sides. The corners for the chromosome shape in Figure 10 are shown in the linked edge image in Figure 10 (b) with their angle directions.

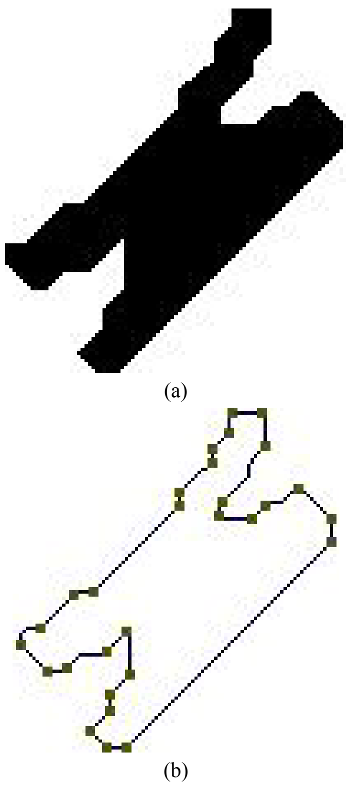


Figure 10: Detected corners for a chromosome shape: (a) Chromosome shape, (b) Linked edge image.

The global algorithm starts with the straight edge detector, detects the straight edges of every contour in the image, and reports the intersection of every two non collinear straight lines as corners. Then, the polygonal approximation algorithm examines every contour, selects from its corners the dominant ones that form a polygon that best fit it.

Thus, the goal of our polygonal approximation algorithm is to find the optimal polygon, approximating the contour of a given shape, given a required compression ratio CR:

$$CR = {}^{n}/_{nc} \tag{1}$$

where n is the number of shape's edge points and nc is the number of selected corners called dominant corners that form the polygon vertices. At a given CR, the objective function is to minimize the global integral square error (ISE) which is the sum of squared distance of each contour's edge point to the nearest approximated polygon segment. The ISE of a polygon's segment corresponds to the area of the region bounded between it and the corresponding edge part. For a particular shape as in Figure 11, since n is constant CR becomes a function of nc only. Therfore, the problem is limited to obtain the minimal possible ISE for a given number of dominant corners nc. In general, the entry of the algorithm is the parameter CR, nc will be calculated automatically for every contour.

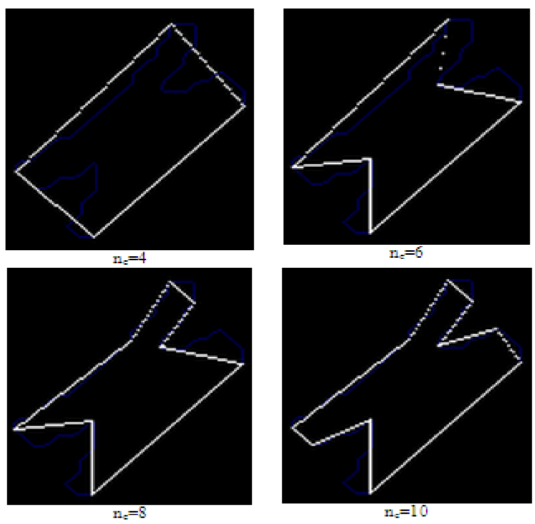


Figure 11: Polygonal Approximation at various nc.

Figure 11 shows the approximated polygon of the chromosome shape used in Figure 10 at various nc. The global ISE decreases while nc increases.

Two parameters are used in the algorithm and should be understood at the beginning. The first one is the local ISE which is the ISE corresponding to a given polygon's segment. The second one is the local ISE variation "LISEV" due to the removal of a corner from the list of polygon's vertices. In Figure 12, at iteration i+1, the LISEV due to the removal of corner Cor3 has the same meaning as LISEV due to the introduction of segment [Cor2Cor4]. The algorithm can be summarized as follows:

- *For a given contour of n edge points and m corners, select all the detected corners as polygon's vertices following the linking order.*
- *The number of dominant corners nc = m.*
- *Iterate until the current CR = n/nc becomes greater than or equal to a specified threshold.*
  - *For each current corner "Corc" from the list of selected corners:*
    - *Find the previous and next selected corners "Corp" and "Corn".*
    - *Calculate the LISEV due to its removal: $LISEV_c$ = new segment LISE – old segments LISEs (see illustration in Figure 12).*
    - *If any of the previously removed corner located between "Corp" and "Corn" has a greater LISE variation ($LISEV_r$) than reselect this corner, remove the current corner "Corc" from the list of vertices and set the final LISEV as $LISEV_r$.*
  - *Remove the corner that corresponds to the minimal LISEV from the list of selected corner.*
  - *Decrement nc by 1.*
- *Calculate the global ISE for the entire polygon which is the sum of LISEs of introduced segments.*

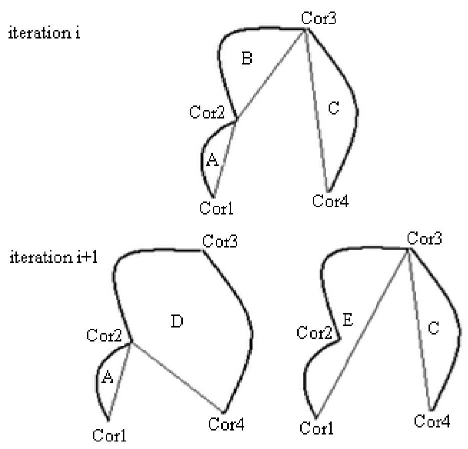


Figure 12: Corner Suppression.

Starting by considering all the corners as polygon's vertices, the idea behind the ICS algorithm is to decrease the number of vertices iteratively of the approximated polygon. Here, the suppressed corner (vertex) is the one that its suppression will cause the minimal increase to the current global ISE and this will ensure the selection of the optimal polygon at every iteration (at every value of *nc*). Consider the case presented in Figure 12. We have four selected corners at iteration *i* so there are three polygon's segments with their corresponding LISE represented by the areas A, B and C. The idea is to calculate the LISEV caused by the removal of one of the two corners Cor2 or Cor3, for example, at iteration *i*+1. D is the area that represents the LISE of Cor3 and E is the one that represents the ISE of Cor2. The removal of Cor3 will add a new polygon's segment [Cor2Cor4] and eliminate two others [Cor2Cor3] and [Cor3Cor4]. Therefore, we can write

$$LISEV_3 = D - (B + C) \quad (2)$$

Same procedure will apply for calculating the LISEV caused by the removal of Cor2 with:

$$LISEV_2 = E - (A + B) \quad (3)$$

If $LISEV_3$ is smaller than $LISEV_2$ than Cor2 will be removed otherwise Cor3 will be removed.

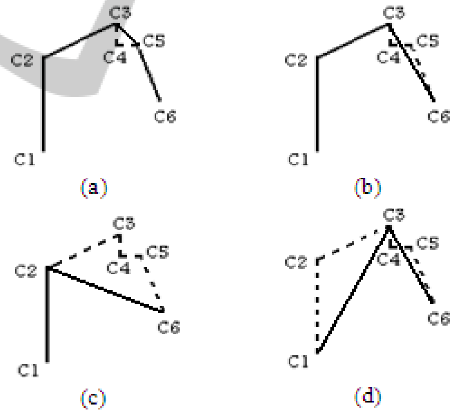


Figure 13: Corner Reselection.

While the corners are suppressed one after the other, the LISEV of a corner that depends on the current corner "*Corc*" and the directly selected neighboring corners (previous one "*Corp*" and next one "*Corn*"), may change since "*Corp*" or "*Corn*" may also change. So we should always update and then check the LISEV of even the suppressed corners to ensure the optimality of the suppression at each iteration. This can be illustrated using the list of corners shown in Figure 13 where all the five corners are selected initially. This is a tested case by the algorithm where C4 (Figure 13 (a)), C5 (Figure 13 (b)) then C3 (Figure 13 (c)) are suppressed iteratively first and the remaining polygon has only C1, C2 and C6 as vertices. Now if we calculate the LISEV of removing C2 and that of removing C3, C4 and C5 taking C1 as "*Corp*" and C6 as "*Corn*", we find that the LISEV of removing C3 is the greatest one. So we should suppress C2 and reselect C3 (Figure 13 (d)). Then, the LISEV resulting from adding [C1C6] is that of removing C3 and it will be compared with the LISEV of removing the remaining selected corners existing on the whole contour to deselect the corner with the minimal one.

5 EXPERIMENTAL RESULTS

Our proposed algorithm is tested on three different shapes shown in Figure 14: (a) Chromosome, (b) Leaf and (c) semicircles (The and Chin 1989). The results obtained are compared to those presented in various papers (Parvez and Mahmoud 2010, Carmona-Poyato, Madrid-Cuevas, MedinaCarnicer and Munoz-Salinas 2010, Marji and Siy 2004 and Masood 2008).

Other than the ISE, a new parameter is introduced for the comparison: the weighted sum of square error WE given by

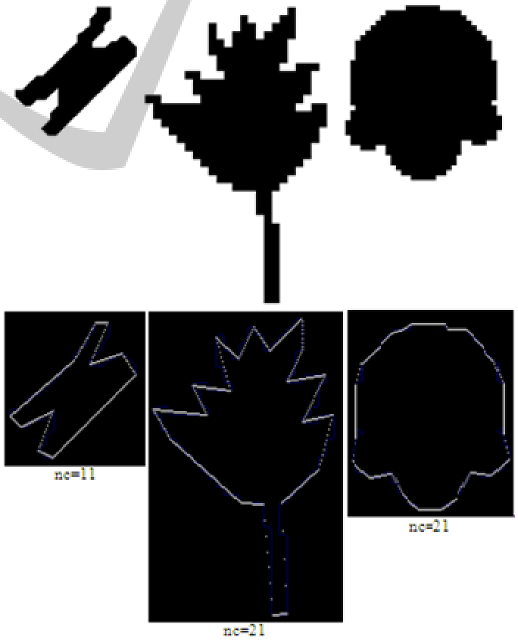
$$WE = {}^{ISE}\!/_{nc} \tag{4}$$

Since our algorithm requires a colored or grey image as an input not only a digital image or edge image while the others are tested directly on a digital image, we need a unique platform for comparison. From here, we have selected manually on the edge image derived by our algorithm the vertices of the polygon reported by each method in (Parvez and Mahmoud 2010, Carmona-Poyato, Madrid-Cuevas, MedinaCarnicer and Munoz-Salinas 2010, Marji and Siy 2004 and Masood 2008), then calculate the corresponding ISE and show the results in Table 1.

From Table 1, it can be seen clearly that our algorithm has better *ISE* and *WE* compared to others. This is due to three main reasons. The first one is the excellent location of the corners due to the efficient straight edge detector. So, the optimal polygon is the one whose vertices are selected among these corners. The second one is the efficient technique to select the best corners as polygon vertices that will lead to the minimal error (*ISE*) at a specific *nc*. The third one is the update of the LISE, at each iteration, even for previously suppressed corners. This feedback will ensure that, when eliminating a corner or selecting a new segment, the maximal LISE is set for this segment. This fact will show the real LISEV caused by selecting this segment and as a result will ensure the selection of the segment with the real minimal LISEV.

Table 1: Comparative Results for the Chromosome, Leaf and semicircle shapes.

Contour	Method	n_c	CR	ISE	WE
Chromosome (n=296)	Marji and Siy [20]	10	29.6	546.2	54.6
	Cammona-Povato et al [19]	12	24.6	439.9	36.6
	Masood [21]	12	24.6	302.5	25.2
	Parvez and Mahmoud [18]	11	26.9	586.9	53.3
	Our Method	10	29.6	429.5	42.9
		11	26.9	370.9	33.7
		12	24.6	302.5	25.2
Leaf (n=840)	Marji and Siy	17	49.4	2124.4	124.9
	Cammona-Povato et al	21	40	1396.2	66.5
	Masood	23	36.5	1203.1	52.3
	Parvez and Mahmoud	23	36.5	1264.9	55.0
	Our Method	17	49.4	2089.9	122.9
		21	40	1250.2	59.5
		23	36.5	1192.3	51.8
Semicircles (n=461)	Marji and Siy	15	30.7	789.5	52.6
	Cammona-Povato et al	21	21.9	490.1	23.3
	Masood	26	17.7	334.1	12.8
	Parvez and Mahmoud	14	32.9	957.2	68.4
	Our Method	14	30.7	574.5	41.0
		21	21.9	347.3	16.5
		26	17.7	270.0	10.4



(a) (b) (c)

Figure 14: Tested Shapes and their polygonal approximations at a particular *nc*.

For a real image that contains more than one shape or contour, *nc* cannot be fixed and considered as an input for the algorithm since existing contours maybe best approximated by polygons of different number of vertices. In other words, *nc* cannot be fixed for all contours. Here, *CR* or *WE* plays the big role and must be used both or at least one of them as inputs. By specifying a threshold for the *WE* parameter used as an input, the role of a polygonal approximation algorithm becomes to find the greatest *nc* per contour that corresponds to the greatest *WE* less than the specified threshold. Here the *CR* is an output. On the other hand, by specifying a threshold for *CR* used as an input, the goal still to find the greatest *nc* per contour, that corresponds to the minimal *CR* greater than the threshold. In this case, *WE* is an output. So the choice of selecting which parameter or maybe both depends on the specific application.

Finally, Figure 14 shows the polygons approximating the tested shapes at a given *nc*. It can be seen clearly that the results are very precise.

Finally, we suggest an application based on DCs which is shape recognition of 2D objects dedicated for a robot embedded with a vision system where our polygonal approximation's algorithm is implemented. The goal is to present first a 2D shape to the robot and then it tries automatically to locate it in a simple scene.

To simulate this experiment, we present two images to the algorithm; the first one is a training image, shown in Figure 15, containing only the desired shape and the second one is a test image containing a scene of multiple shapes as shown in Figure 16 (a).

For the training image, the algorithm detects the DCs located on the shape's contour. For the test one, it detects and groups the DCs per contour representing each shape. After that the matching procedure starts by comparing every test group of DCs with the trained DCs using the DC angle and ratio of the lengths of their sides as matching parameters.

Figure 15: Training image.

This matching criterion remains feasible when the image transformation that relates the two images is a translation-rotation, similarity or conditioned affinity. In general, an affine transformation preserves ratio but does not preserve angles (Hartley and Zisserman, 2003) so the matching criterion does not hold for this type of transformation only if the camera plane and the shape plane are parallel (Hartley and Zisserman 2003); in this case, the angles are nearly preserved. This is the conditioned affinity.

The result of matching is shown in Figure 16 (b) where the DCs are shown only on the matched shape's contour which is the star shape.

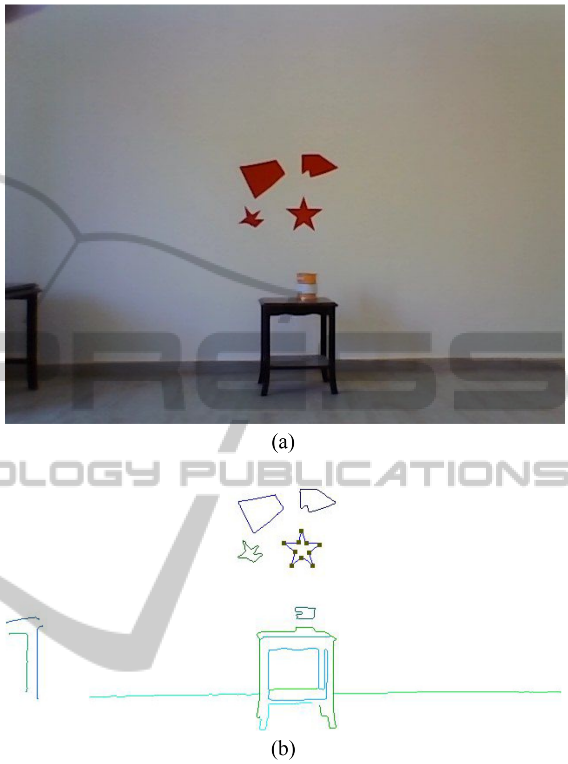


Figure 16: (a) Test image. (b) Corresponding Image of contours with DCs shown on matched contour.

6 CONCLUSIONS

In this paper, a new polygonal approximation technique is proposed. It is composed of two procedures. The first is called "Straight Edges Detector" which examines all the contours existing in the input image and detects the edge parts that can be considered as straight edges. These straight edges are straight lines that exist frequently at the borders of various objects in real scenes especially human made environments like buildings, cars, doors… The importance of detecting these straight edges remains in their role of detecting edge corner points. The intersection of two non collinear straight edges of appropriate length (greater than a threshold) is reported as a corner.

The second part of our work is a polygonal approximation algorithm that takes the detected corners as an entry. By fixing an entry parameter like

Compression ratio *CR* or weighted sum error *WE*, the algorithm starts, per contour, by removing iteratively the corners that introduce the minimal possible ISEV to the global ISE measure until reaching the stopping criterion. At the end, the remained corners form the vertices of the polygon that can best approximate the current contour.

The experimental results have shown good results in comparison with other existing methods. In our opinion, this is due to the efficient straight edge detector that explores all the contour corners efficiently and then to the iterative polygonal approximation algorithm that removes, at each iteration, the corner with the smallest LISEV and at the same time updates and reexamines the LISEV of already removed corners. This way, we can ensure that the remained corners form the polygon that best fit their contour.

Finally, as a future work, we suggest an image registration application that can benefit from detected straight edges and corners. These image features can be combined together in a certain number to form specific shapes or primitives that can have invariant measures versus different image transformation.

REFERENCES

Loncaric, S., 1998. *A survey of shape analysis techniques*, Pattern Recognition, vol.31.

Herman M., Kanade T. and Kuroe S., 1984. *Incremental Acquisition of a Three-Dimensional Scene Model from Images*, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. Pami-6, No. 3.

Bouchafa S. and Zavidovique B., 2006. *Efficient cumulative matching for image registration*. Image and Vision computing, Vol. 24.

Ayache N. and Faugeras O., 1986. *A new approach for the recognition and positioning of two dimensional objects*, IEEE Transaction on Pattern Analysis and Machine Intelligence, vol.8.

Nachar R., Inaty E., Bonnin P. and Alayli Y., 2012. *A Robust Edge Based Corner Detector*, Submitted for possible publication in Autonomous Robots Springer, September 2013, under review.

Dunham J.,1986. *Optimum Uniform Piecewise Linear Approximation of Planar Curves*, IEEE Trans on Pattern Analysis and Machine Intelligence vol PAMI 8 n°1, pp 67-75.

Pavlidis T., 1982. *Algorithms for Graphics and Image Processing*, Springer Verlag.

Wall K. and Danielsson P., 1984. *A fast sequential method for polygonal approximation of digitized curves*, Computer Vision Graphics and Image Processing, vol 28, pp 220-227.

Gupta A., Chaudhury S. and Parthasarathy G., 1992. *A Hough Transform Based Approach to Polyline Approximation of Object Boundaries*, Proceedings. 11th IAPR International Conference on Pattern Recognition. Vol.III. Conference C: Image, Speech and Signal Analysis.

Mikheev A., Vincent L. and Faber V., 2001. *High-Quality Polygonal Contour Approximation Based on Relaxation*, Pr ceedings Sixth International Conference on Document Analysis and Recognition.

Prewitt J., 1979. *Object enhacement and extraction, Picture processing & psychopictorics*, BS Lipkin&A.Rosenfelded, Academic Press, New York USA.

Sobel, 1978. *Neighbourhood coding of binary images for fast contour following and general binary array processing*, Computer Graphics & Image Processing USA, vol 8 pp 127-135.

Kirsch R., 1971. *Computer determination of the constituent structure of biological images*, Computers and Biomedical Research 4.

Kolesnikov A., 2008. *Fast Algorithm for ISE-Bounded Polygonal Approximation*, 15th IEEE International Conference on Image Processing.

Kolesnikov A., 2009. *Minimum Description Length Approximation of Digital Curves*, 16th IEEE International Conference on Image Processing.

Kolesnikov A., 2011. *Nonparametric Polygonal and Multimodel Approximation of Digital Curves with Rate-Distortion Curve Modeling*, 18th IEEE International Conference on Image Processing.

Pinheiro A., 2010. *Piecewise Approximation of Contours Through Scale-Space Selection of Dominant Points*, IEEE Transaction on Image Processing, Vol. 19, No. 6.

Parvez M. T. and Mahmoud S. A., 2010. *Polygonal Approximation Of Planar Curves Using Triangular Suppression*, 10th International Conference on Information Science, Signal Processing and their Applications.

Carmona-Poyato A., Madrid-Cuevas F.I., MedinaCarnicer R. and Munoz-Salinas R., 2010. *Polygonal approximation of digital planar curves through break point suppression*, Pattern Recognition, 43(1), pp. 14-25.

Marji M. and Siy P., 2004. *Polygonal representation of digital planar curves through dominant point detection – a nonparametric algorithm*, Pattern Recognition 37, pp. 2113- 2130.

Masood A., 2008. *Optimized polygonal approximation by dominant point deletion*, Pattern Recognition 4 1, pp. 227- 239.

The C. H. and Chin R.T., 1989. *On the detection of dominant points on digital curves*, IEEE Transactions of Pattern Analysis and Machine Intelligence 11, pp. 859-872.

Canny J., 1986. *A computational approach to edge detection*, IEEE Transactions of Pattern Analysis and Machine Intelligence., vol. PAMI-8, pp. 679–698.

Deriche R., 1987. *Optimal Edge detection using recursive filtering*, Int journal on Computer Vision.

Hartley R. and Zisserman A., 2003. *Multiple View Geometry in Computer Vision*, Cambridge university press, 2nd Edition.