

Unique Measure for Geometrical Shape Object Detection-based on Area Matching

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ABSTRACT

Object classifier often operates by making decisions based on the values of several shape properties measured from an image of the object. The paper introduces a unique definition of measure for 2-D geometrical object shape detection. Using this definition different object shapes can be identified on the basis of their degree of fitness parameter. Basically, we have fitted a 2-D polygon/curve on the object as a best fitted polygon/curve and computed the parameter degree of fitness which is the ratio of the matching area and non-matching area due to the fitted polygon/curve and the object both. The results show the effectiveness of the proposed measure.

Keywords: Measure, shape detection, pattern recognition, circular fit, elliptic fit, rectangular fit

1. INTRODUCTION

A major task in image analysis is the discrimination of objects based on their appearance. Various properties of appearance can be measured falling into such categories as texture, color and shape. Shape is obviously a powerful tool for describing and differentiating objects and has been extensively applied in many areas of computer vision. Several geometric shape properties are measured for recognition and description of two-tone objects in digital grid. Of these properties circularity, ellipticity, square-ness and rectangular-ness play important roles in the applications involving industrial parts inspection, biomedical image analysis^{1,2}, and target detection^{3,4}. Many industrial manufacturing processes depend on the accurate measurement of circular shapes for example, pipe, tube and ball and roller bearings to ensure that the components satisfy the engineering tolerance standards⁵.

Different definitions of measures are available for different object shapes detection. Even feature based approaches although potentially being based on local features requires the presence of most of the object to compute the statistic of the features. It applies to all shape descriptors presented in the special issue of pattern recognition on shape similarity by Latecki⁷, *et al.* as well as to the shape descriptors presented in Belongie⁸, *et al.* and Grigorescu and Petkov⁹. The subject of shape perception remains a fertile area of research. The power of such primitive shapes for scientific analysis is that they can be applied to a vast range of tasks involving not only man-made objects but also natural forms. For example, the ellipse has recently been used to model apple bruising¹⁴, corneal shape¹⁵, cross-sections of trees¹⁶, faces¹⁷, etc.

In computer vision, circularity is extensively used as a shape measure^{6,18}. Haralick⁶ proposed a measure for circularity where the center of the fitting circle is assumed to coincide with the centroid of the object border. But there is little work on the measurement of the other shapes. Proffitt¹⁹ and Peura

and Livarinen²⁰ have both described ellipticity measures. Although one rectangularity measure¹⁸ is reasonably well known it is not as widespread as circularity. More recent work by Rosin described several new approaches to rectangularity measurement²¹. Another recent work by Rosin²² proposed several algorithms for calculating ellipticity, rectangularity and triangularity shape descriptors. It appears no unique definition of measure applicable generally is available for different geometrical object shape detection. Nayak and Stojmenovic²⁷ proposed a variety of schemes that compute global shape measures, which can be categorised as techniques based on minimum bounding rectangles, other bounding primitives, fitted shape models, geometric moments, and Fourier descriptors are described. Farin²⁸ compared a variety of triangle shape measures using concepts such as smoothness and convexity. Stojmenovic and Nayak²⁹ proposed several measures, all of which are based on existing linearity measures that have been adapted to measure circularity. To make use of these linearity measures, they transferred the Cartesian coordinates of the input set into polar coordinates. The linearity of the polar coordinate set corresponds to the circularity of the original input set given a suitable centre. They separately considered the circularity of ordered and unordered point sets. The circularity of unordered data is determined directly from the linearity measure, whereas the circularity of ordered data is derived by multiplying the unordered data circularity measure by a monotonicity factor. A shape descriptor based on the histogram matrix of pixel-level structural features is presented in Zhang and Wenyin's paper³⁰. In this paper first, length ratios and angles between the centroid and contour points of a shape are calculated as two structural attributes. Then, the attributes are combined to construct a new histogram matrix in the feature space statistically. The proposed shape descriptor can measure circularity, smoothness, and symmetry of shapes, and be used to recognise shapes. Stojmenovic, and Nayak³¹ proposed a method of measuring

the accuracy of ellipse fits against the original point set. The evaluation of fits proceeds by their ellipticity measure which transforms the point data into polar representation where the radius is equal to the sum of distances from the point to both foci, and the polar angle is equal to the one the original point makes with the centre relative to the x -axis. The linearity of the polar representation will correspond to the quality of the ellipse fit for the original data. They also proposed an ellipticity measure based on the average ratio of distances to the ellipse and to its centre.

Author has proposed a new definition of measure for geometrical object shape detection in this paper. The proposed definition of measure is a unique measure applicable generally by which different object shapes can be identifying on the basis of their degree of fitness parameter. First, we have fitted a polygon/curve on the object as a best fitted polygon/curve. Then we have computed the parameter degree of fitness. Then we identify the object of a particular geometrical shape on the basis of minimal degree of fitness value.

2. BEST FITTING METHODS OF 2-D PARAMETRIC POLYGONS/CURVES

Computing geometrical features is an important intermediate level vision task that has many applications. This step serves as a gateway to high-level matching and understanding of elements in the image. Among many other 2-D parametric polygons/curves fitting of rectangle/square, circle, and ellipse plays important roles in real life applications. In general, approaches for locating parametric polygons/curves can be divided into two steps¹⁰⁻¹². The first step is to detect the boundary of the object. The second step is to estimate its parameters based on the boundary points^{10-12,25} and the parameters estimation procedures are discussed step by step briefly.

2.1 Best-fitted Rectangle

Fitting of rectangle is important in shape detection, objection detection (e.g. building) and many other application areas. We have used our previous algorithms^{10,25} for computing the best-fitted rectangle for closed regions. The coordinates of the vertices of the best-fitted rectangle are computed using a bisection method of the upper estimated rectangle (UPER) vertices and the under estimated rectangle (UNER) vertices based on difference area minimisation between object and best-fitted rectangle areas. The coordinates of the vertices of UPER and UNER are computed directly using closed-form solutions based on the border points of the object. The approaches for UPER and UNER are based on simple coordinate geometry and least square fitting approach. Using a least square approach we determine the directions of major and minor axes of the object, which gives the orientation of the object. The four vertices of UPER are computed by pair-wise solving the four straight lines¹⁰. Also the four vertices of UNER are computed by pair-wise solving the four straight lines, which are formed by least square fitting approach²⁵. Finally, the four vertices of the best-fitted rectangle are computed by bisection method of the UPER and UNER vertices in a iterative way based on the constraint of area unchanged of the fitted rectangles between

the last and previous iterations, which is same as the difference between the area of the object and the area of the best-fitted rectangle is minimum²⁵.

2.1.1 Computing Upper Estimated Rectangle

There are four steps in our UPER finding approach¹⁰. We begin with a segmented image in which each region is labeled. We briefly summarise the steps here.

- (a) First compute boundary points of the object.
- (b) The centroid, major and minor axes of the object is estimated by using the boundary points of the object.
- (c) The upper and lower furthest points with respect to major axis and the corresponding points with respect to minor axis are determined.
- (d) Computing the vertices for UPER by solving the four lines pairwise through the above four furthest points.

2.1.2 Computing Under Estimated Rectangle

There are six steps in our UNER finding approach²⁵. We briefly summarise the steps here-

- Step 1:* Starting with the segmented image, first compute boundary points of the object.
- Step 2:* Using all points of the object, compute the centroid of the object.
- Step 3:* Find the major and minor axes of the object.
- Step 4:* Find the upper and lower edge points with respect to major and minor axes.
- Step 5:* Find two lines parallel to the major axis, which are the best-fitted lines among the upper and lower edge points respectively with respect to major axis separately by least square method. Similarly, find the corresponding lines parallel to the minor axis.
- Step 6:* Find the intersection of the lines (pairwise) to determine the vertices of the UNER.

2.1.3 Best-fitted Rectangle

```
BestFitRectangle() {
    Find area of the object,  $A_{obj}$ ; Find UPER and UNER
    Compute areas of UPER ( $A_{up}$ ) and UNER ( $A_{un}$ )
    do {
        if  $A_{un} > A_{obj}$  {
             $A_{old} = 0$ ;
            Replace the all UNER vertices with CENTROID;
             $R_{mid} = \text{BISECT}(\text{UNER}, \text{CENTROID})$ ;
        }
        else {
             $A_{old} = A_{un}$ ;  $R_{mid} = \text{BISECT}(\text{UNER}, \text{UPER})$ ;
        }
         $A_{mid} = \text{Area}(R_{mid})$ ;
        if  $A_{mid} > A_{obj}$  {
            UPER =  $R_{mid}$ ;  $A_{up} = A_{mid}$ ;
        }
        else {
             $R_{mid} = \text{UNER}$ ;  $A_{mid} = A_{un}$ ;
        }
         $A_{old} = A_{mid}$ ;
    }
```

```

} while (Aold # Amid)
}
    
```

Upper estimated rectangle is the minimum bounding rectangle and hence the area of UPER is always greater than or equal to the area of the object. In addition, UNER is normally inside the bounded region and the area of UNER in such cases is less than the area of the region. Earlier, we have proposed a method for finding best-fitted rectangle of a bounded region so that the area difference between the fitted rectangle and object is the minimum²⁵ which is briefly described as above.

In the above algorithm, BISECT function finds the intermediate rectangle that is halfway between two rectangles. The algorithm converges when the area of the intermediate polygon does not change in successive iterations. In this situation, the difference between the area of best-fitted rectangle and the area of the object is the minimum. We have proved the convergence of the algorithm using the notion of roots in the theory of equation²⁵.

2.2 Elliptic and Circular Fit

Fitting circles and ellipses of an object is a problem that arises in many application areas. Our ellipse or circle computation¹² begins with finding the boundary points¹⁰⁻¹² for each blob. The border points of a perfect elliptical or circular object will satisfy the equation of the ellipse or circle and in such situation the error due to fitting will be zero. But if the border point of an object does not lie on the fitted ellipse or circle then it will generate an error. Here, we define an error function for all border points of the object and estimate the other parameters of ellipse or circle by minimising the error¹².

3. EXISTING MEASURE OF DIFFERENT SHAPES

Measure plays important roles in many image processing and pattern recognition problems, especially in man-made object detection and shape detection of medical imagery. Different definitions of measures are available for different geometrical shape objects detection. Here, we are briefly describing them one by one.

3.1 Rectangularity

Various measures of square-ness/rectangular-ness are available²¹ and few of them are like side based, rectangular dependency, moment matching, minimum bounding rectangle (MBR). The MBR of a convex polygon can be calculated in linear time by Toussaint's²⁶ rotating caliper method. In an attempt to overcome the sensitivity of the MBR to noise Rosin^{21,22} described an alternative in which a rectangle is fitted to the region based on its moments. Rectangularity is then measured as the normalised discrepancies between the areas of the rectangle and the region.

3.2 Circularity

Over recent years, a number of geographers have tried to find ways of defining the shape of an area¹³. In particular, they have tried to devise a measure of compactness or circularity. Figure 1 shows an example of two islands. Island B is more compact or circular than island A. Compactness or circularity

has nothing to do with the size of the island. We have small compact-island or large compact-island. We could say that a shape is more compact or circular if it has a smaller perimeter for a given area.

A measure of compactness is¹³ $Compactness = Area \div Perimeter$. Six islands A, B, C, D, E and F are shown in Fig 2. Table 1 shows the values of compactness or circularity of different shape islands.

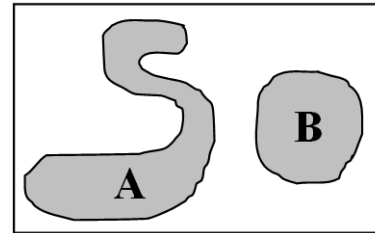


Figure 1. Example of compact and elongated shape objects.

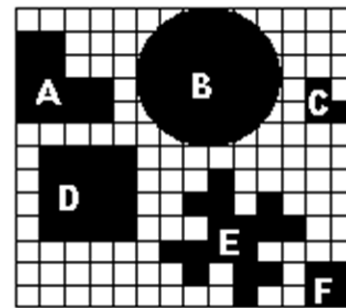


Figure 2. Example of different shape islands.

Since, the above definition is not dimensionless so it will give different results for enlargements of shapes. Thus, in this example, D and F are both squares but they give different measurements of compactness (similarly with A and C). To overcome this problem a better measure of circularity has been defined as $Circularity = Area \div Perimeter^2$.

This is dimensionless and last row of Table 1 shows the corresponding values of circularity or compactness of all six islands of Fig 2. We have seen from Table 1 that B is most compact/circular. D and F are tie, A and C are tie and E is least compact/circular.

Table 1. Values of circularity of different islands

Shape	Area	Perimeter	Area/perimeter	Area/perimeter ²
A	12	16	0.75	0.047
B	28.26	18.84	1.5	0.080
C	3	8	0.375	0.047
D	16	16	1	0.063
E	16	32	0.5	0.016
F	4	8	0.5	0.063

The ratio $4pA/P^2$, where A and P are area and perimeter, is quoted in Swan and Ridgway¹³ as the circularity ratio (measure) so that, it ranges from 0 to 1. A perfectly compact shape should have a measure of 1, while a long thin shape should have a measure near to 0. One criticism of its use by geographers is that it is difficult to define and calculate the perimeter of a very large irregular boundary such as a country or a river basin.

Fractal geometry might suggest that such perimeters may even be infinite.

Other measures of circularity¹³ are form ratio, radius ratio, compactness ratio, radius-standard deviation ratio⁶.

3.3 Ellipticity

Few measures of ellipticity are available in the literature^{20,22}. One approach is based on moment invariants. Since, any ellipse can be obtained by applying an affine transform to a circle, Rosin²² used the simplest affine moment invariant of the circle to characterise ellipses and the other one is elliptic variance²⁰.

4. UNIQUE DEFINITION OF MEASURE

There is no single definition is available in the literature which can be used for finding the shape of an object. As for example, for finding rectangular or circular or elliptical shape object one has to define different measure for different shape. In this paper, we propose a unique definition of measure for rectangularity, circularity and ellipticity by which different shape (rectangle, circle and ellipse) of objects can be identify on the basis of their degree of fitness parameter. Here, ‘unique definition’ means ‘single definition’ by using this definition one can identify an object shape based on the degree of fitness (as shown in Figs 4 and 5). It is a relative measure on the basis of the fitted curve/polygon. First, we have fitted a rectangle/circle/

ellipse optimally on the object and then compute the parameter degree of fitness. The object can be identifying as rectangle/circle/ellipse on the basis of minimum degree of fitness value. The proposed measure should be more robust in the presence of small area deviations in the boundary.

There are five steps in our approach. We begin with a segmented image in which each region is labeled. Without loss of generality we assume that there is only one region in the image. We first fit a polygon/curve (rectangle/circle/ellipse) on the object. Figure 3(a) shows an image (object) and its fitted circle is shown in Fig 3(b). Next step is to find the matching area. Figure 3(c) shows the matching area (dark black region) of the object and the fitted circle. We then find the non-matching area due to fitted circle and it is shown in Fig. 3(d) (dark regions inside the circle upper and lower portions). Next, we find the non-matching area due to object and shown in Fig. 3(e) (little bit bright gray regions inside the object left and right sides). The total non-matching area is the sum of both non-matching areas due to object and curve. Then we compute the degree of fitness as the ratio of non-matching area and matching area. Mathematical formulation of the proposed definition is as follows.

Let A be a region and B be the fitted polygon/curve (rectangle/circle/ellipse). Without loss of generality we assume that the area of a region means the number of points of the

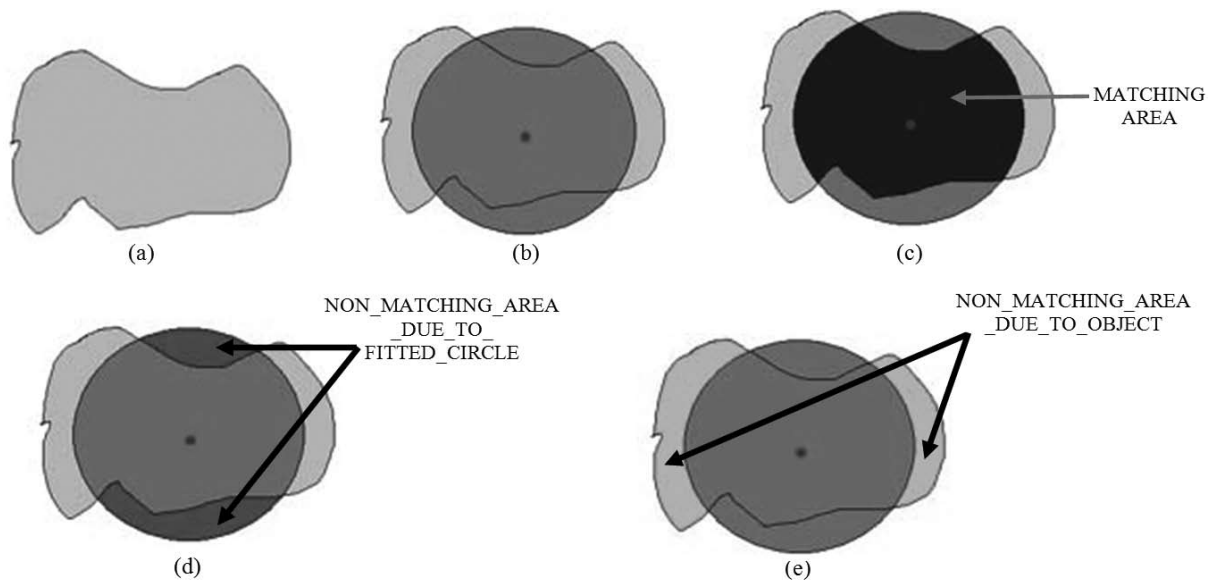


Figure 3. Example of an object. (a) Object, (b) Fitted circle, (c) Match area of the object and fitted circle, (d) Non-match area with respect to circle, and (e) Non-match area wrt object.

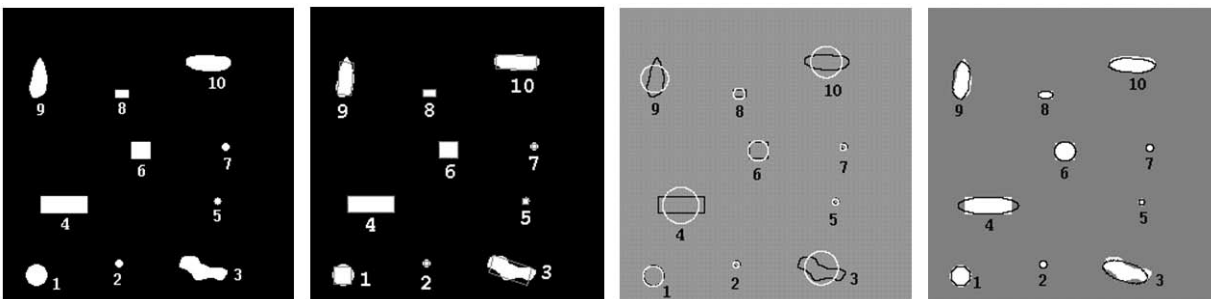


Figure 4. (a) Different shapes binary image, (b) Fitted rectangle, (c) Fitted circle, and (d) Fitted ellipse.

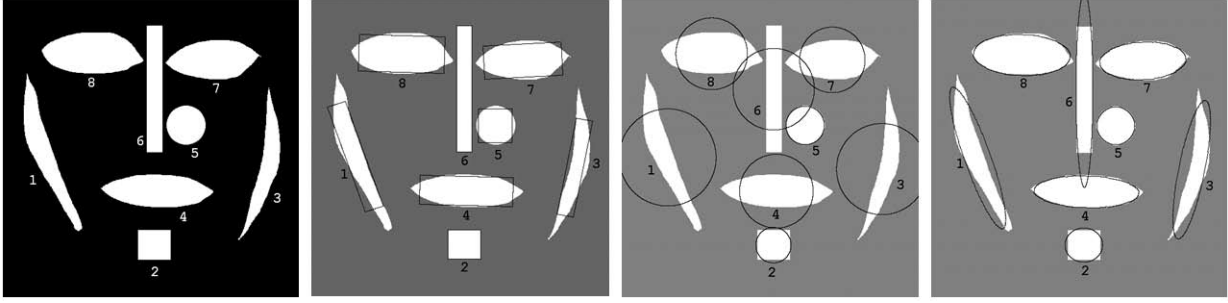


Figure 5. (a) Different shapes binary image, (b) Fitted rectangle, (c) Fitted circle, and (d) Fitted ellipse.

object. Similarly, the area of the polygon/curve (rectangle/circle/ellipse) is the number of points inside the polygon/curve including the boundary points. The matching region of A and B is $A \cap B$. The non-matching region due to object is $A - (A \cap B)$ and the non-matching region due to fitted curve is $B - (A \cap B)$. Let $\#A$ be the area of region A and let M_A^B is called the measure of degree of fitness of object A wrt fitted polygon/curve B . So the measure of degree of fitness M_A^B is defined as

$$M_A^B = \frac{\text{Total non-matching area}}{\text{Matching area}} = \frac{\#[B - (A \cap B)] + \#[A - (A \cap B)]}{\#(A \cap B)}$$

“+” means union, so from the set theory

$$[B - (A \cap B)] \cup [A - (A \cap B)] = (A \cup B) - (A \cap B)$$

$$\text{so } M_A^B \text{ can be written as } M_A^B = \frac{\#[(A \cup B) - (A \cap B)]}{\#(A \cap B)}$$

The proposed measure of degree of fitness M_A^B depends on fitted polygon/curve (rectangle/circle/ellipse). Since, our fitted polygons/curves in section 2 are invariant under translation, rotation and scaling, so the measure of fitness is also invariant under translation, rotation and scaling. Also, the proposed measure of fitness is dimensionless and always finite since denominator i.e. matching area will never zero. If an object is perfectly fitted with a particular polygon/curve (rectangle/circle/ellipse) then non-matching area will be zero and in that case measure of fitness is zero. So if the measure of fitness of an object due to a particular polygon/curve is zero then the object is the corresponding fitted polygon/curve. Now, we are describing the algorithm for finding the object shape (rectangle/circle/ellipse) as follows.

4.1 Algorithm: Shape Recognition for 2-D Object

Step 1: Fitting rectangle, circle and ellipse of an object in a binary image.

Step 2: Find degree of fitness according to the proposed definition of measure for rectangle, circle and ellipse. Let M_A^R , M_A^C and M_A^E are the degree of fitness for rectangle, circle and ellipse for an object A , respectively.

Step 3: Find the minimum among M_A^R , M_A^C and M_A^E . Let M_A^{2D} be the minimum value of degree of fitness for object A . That is, $M_A^{2D} = \min[M_A^R, M_A^C, M_A^E]$.

Step 4: If $M_A^{2D} = M_A^R < T$ (where T is the predefined threshold)

and opposite sides are equal and adjacent sides are not equal of the fitted rectangle then the object A is rectangular object. If $M_A^{2D} = M_A^R < T$ and all sides are equal of the fitted rectangle then the object A is square object. T is called the *tolerance level* of degree of fitness.

Step 5: If $M_A^{2D} = M_A^C < T$ then the object A is circular object.

Step 6: If $M_A^{2D} = M_A^E < T$ then the object A is elliptical object provided lengths of semi-major and semi-minor are not equal. If lengths are equal then the object A is circular object.

Step 7: If $M_A^{2D} = M_A^C = M_A^E < T$ and the lengths of semi-major and semi-minor are equal then the object A is circular object. Otherwise the object A is elliptical object.

It is noted that the tolerance level of degree of fitness T should be very small. We have studied by various images that if $T < 0.3$ then it is better for decision making.

5. RESULTS AND DISCUSSION

To test the effectiveness of the proposed algorithm, we analyse a set of synthetic data as well as real life remote sensing data in 2-D. We have taken the threshold (*tolerance level*) $T < 0.3$ for all images. Figure 4(a) shows a synthetic binary image with 10 different shape objects. In this image, we have fitted rectangle, circle and ellipse for all objects. They are shown in Figs 4(b), 4(c) and 4(d), respectively. Table 2 shows the degree of fitness by the proposed algorithm for all objects with respect to different polygon/curves (rectangle, circle and ellipse).

It is clear from the Table 2 that the value of degree of fitness of object 1 wrt circle is minimum and the value is less than threshold T (0.3), so object 1 is detected as circle. The minimum values of degree of fitness of objects 2 and 7

Table 2. Degree of fitness of different objects in Fig. 4(a)

Objects	Rectangularity	Circularity	Ellipticity
1	0.299639	0.102662	0.108135
2	0.324324	0.001307	0.001159
3	0.688000	0.867315	0.364269
4	0.000000	0.907479	0.208406
5	0.689655	0.001154	0.001154
6	0.000000	0.212500	0.189427
7	0.324324	0.013270	0.013077
8	0.000000	0.507042	0.517241
9	0.450521	0.812298	0.208459
10	0.213043	0.827778	0.096471

occurred wrt ellipse. But the lengths of semi-major axis and semi-minor axis are equal, so according to the algorithm both the objects 2 and 7 are detected as circles. It is noticed that minimum value of degree of fitness of object 5 is same for both circle and ellipse. But the lengths of semi-major axis and semi-minor axis are same, so the object 5 is detected as circle (according the algorithm). We have seen that the minimum values of degree of fitness of objects 4, 6, and 8 are all 0 (zero) wrt rectangle. So, the objects 4 and 8 are detected as rectangle and since all the sides of the fitted rectangle for object 6 are equal, so the object 6 is detected as square. The objects 9 and 10 are detected as ellipse because the minimum values of degree of fitness for both objects occurred with respect to ellipse. It is noticed that minimum value of degree of fitness for object 3 is due to ellipse but the value is greater than tolerance level T . So, it is not detected as ellipse. But, if the tolerance level is increased than this object will detect as ellipse.

The image with 8 different shape objects is shown in Fig. 5(a). Table 3 shows that the degree of fitness of different shape objects of Fig. 5(a) wrt rectangle, circle and ellipse. It is reflected from Table 3 that the objects 2 and 4 are detected as rectangle and since all sides of the fitted rectangle are equal for object 2, so object 2 is a square. The objects 4, 7 and 8 are detected as ellipse and object 5 is detected as circle. Since the values of degree of fitness for objects 1 and 3 wrt all curves (rectangle, circle and ellipse) are higher and greater than tolerance level ($T < 0.3$), so they are not detected as any of the curves, though the minimum values of the degree of fitness for these objects are for ellipticity.

Table 3. Degree of fitness of different objects in Fig. 5(a).

Objects	Rectangularity	Circularity	Ellipticity
1	1.378815	3.835594	0.615690
2	0.000000	0.207373	0.219076
3	1.288053	3.766476	0.897333
4	0.366713	1.229934	0.049481
5	0.274922	0.0318950	0.032764
6	0.000000	3.661320	0.677681
7	0.442777	0.696997	0.074589
8	0.338803	0.747632	0.064988

Figure 6(a) shows an original IRS – 1C panchromatic image with spatial resolution 5.8m×5.8m of size 335×368. Here, we have applied split-and-merge segmentation technique²⁴ for segmentation of the image. The segmentation result is shown in Fig. 6(b). We are interested in some circular shape objects/same clustered regions (bright and gray both) from the segmented image. Figure 6(c) shows the binary image from the segmented image. Here, the bright and gray circular shape objects labeled values of the segmented image (Fig. 6(b)) are converted as object (value = 255) and rest labeled values of the segmented image (Fig. 6(b)) are background (value = 0). Figure 6(d) shows the area filtered image i.e. remove the region whose area is neither very small nor very high. Here, we choose the regions, which satisfy the relation $9 \leq \text{region_area} \leq 200$.

Circular and elliptical fits of each regions of Fig. 6(d) by our

circular and elliptic fit algorithms¹² are shown in Figs 6(e) and 6(k), respectively. Figures 6(f), 6(g), and 6(h) show the detected circular shape objects from Fig. 6(d) by old definition of circular measure¹³ as Area/ Perimeter² with threshold values 0.6, 0.7 and π , respectively. Whereas, the detected circular shape objects from Fig. 6(d) by the proposed definition of measure of fitness with tolerance level $T < 0.3$ is shown in Fig. 6(i). Fig. 6(j) shows the detected circular shape objects according Haralick's⁶ definition of circular measure with threshold value < 5 . We have seen from the result (Fig. 6(j)) that many circular shape objects are not able to detect. From these results we can draw the conclusion that the proposed definition of measure of fitness gives the better results than the old definition of circular measure¹³ and Haralick's⁶ definition of circular measure. Fig. 6(k) shows the detected elliptical objects according the proposed definition with tolerance level $T < 0.3$. We have seen that the values of degree of fitness wrt circle and ellipse for all objects, which are detected as circular shape objects in Fig. 6(i) are equal. Since, the lengths of semi-major and semi-minor axes are same for all objects, so according to the step 7 of our algorithm (section 4) they are not detected as ellipses in Fig. 6(k).

Figure 7(a) shows another IRS – 1C panchromatic image of size 512×512. Binary image by segmentation algorithm²⁴ with certain regions of interest by area-filtered technique is shown in Fig. 7(b). The detected rectangular objects by proposed definition of fitness with tolerance level $T < 0.3$ are shown in Fig. 7(c).

Over recent years a number of geographers have tried to find ways of defining the shape of an area. We have considered four countries like Czechoslovakia, Austria, Bulgaria and Romania for this purpose. Table 4 shows the calculations of compactness for four countries using different existing definition of measures and the proposed definition of measure. All these measure's results place the countries in a similar order, apart from the circularity ratio, which suggests that Czechoslovakia is more compact than Austria. The order will be reverse according the proposed definition of measure because less value of degree of fitness is more compact. Due to this reason the values are in decreasing order by the proposed definition in Table 4, which are not the same order (increasing) as other definitions but the compactness property order of four countries is same (as other definitions) by the proposed definition with respect to circle as well as ellipse.

Basically, the proposed measure for geometrical shape detection depends on two steps – first, we are fitted a polygon/curve optimally on the object than compute the degree of fitness. The optimal polygon/curve depends on the border points of the object, which are very small compared with the whole object. So, the optimal polygon/curve fitting algorithm is of linear order, $O(m)$, where m is the number of border points. Finally, the parameter degree of fitness detection algorithm is of order $O(n)$, where n is the number of total points. So in overall the proposed definition of measure for geometrical shape detection is of order $O(n)$.

6. SUMMARY

A new definition of measure for geometrical shape detection is presented by authors. The proposed definition is

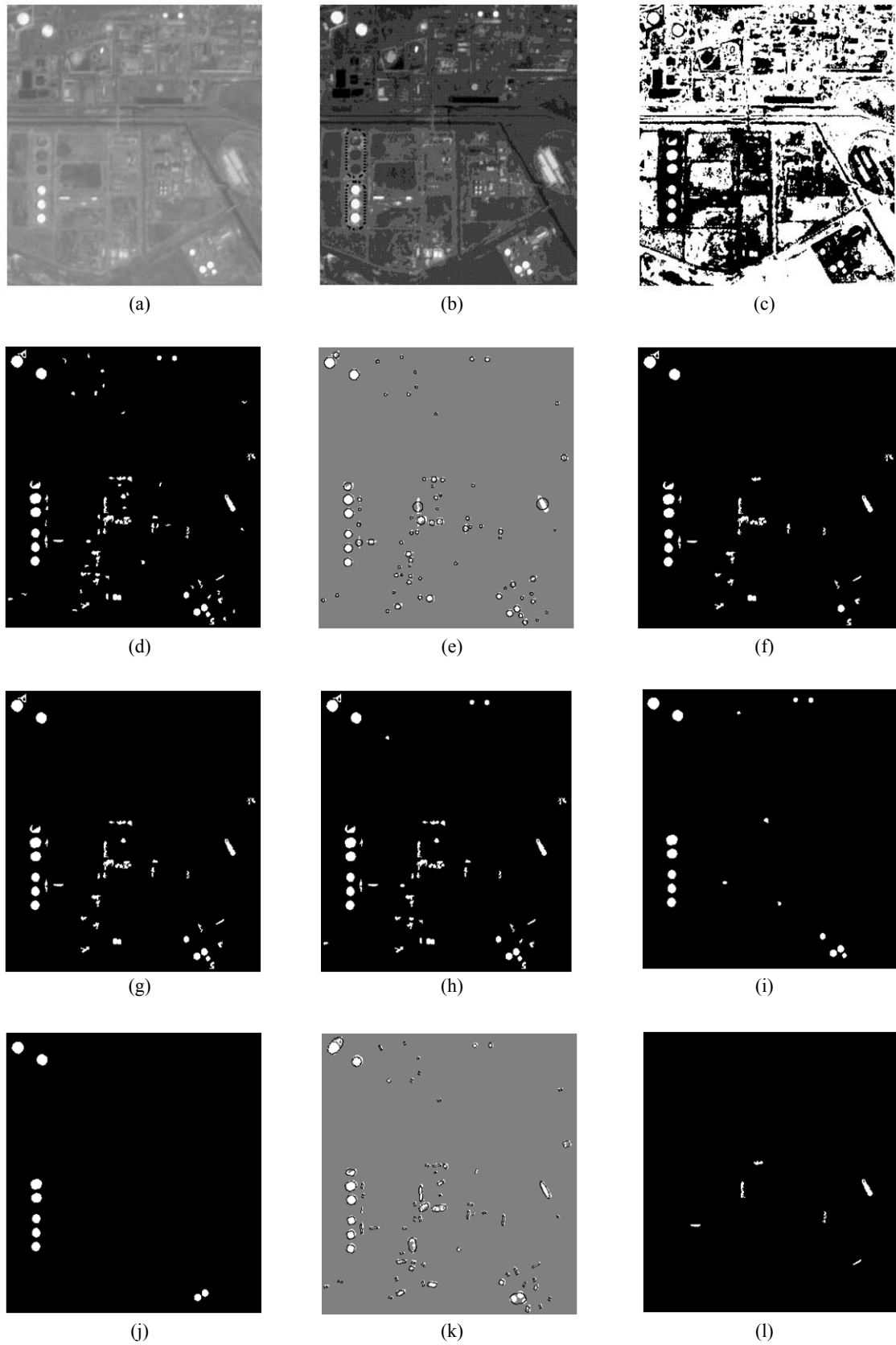


Figure 6. (a) Original Panchromatic image of IRS –1C, (b) segmented image, (c) binary image according the regions of the dotted closed curves bright and dark circular shapes objects from segmented image, (d) area filtered image, (e) fitted circle, (f) circular shape objects according old definition of circular measure with threshold = 0.6, (g) circular shape objects according old definition with threshold = 0.7, (h) circular shape objects according old definition with threshold = π , (i) circular shape object according the proposed definition with threshold < 0.3, (j) circular shape object according Haralick's circular measure⁶, (j) fitted ellipse, and (k) detected elliptical object according the proposed definition.

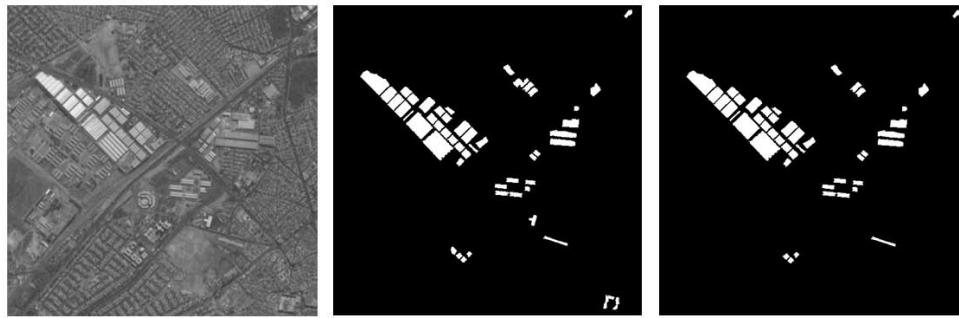


Figure 7. (a) Original Panchromatic image of IRS -1C, (b) binary image by our previous segmentation algorithm²⁴ with certain regions of interest by area filtered technique, and (c) detected rectangular objects according the proposed definition.

Table 4. Compactness properties according to different definition of measures in different countries

Country	Circularity ratio	Form ratio	Compactness ratio	Radius ratio	Proposed definition wrt circle	Proposed definition wrt ellipse
Czechoslovakia	0.330000	0.280000	0.280000	0.280000	1.696408	0.483165
Austria	0.300000	0.300000	0.300000	0.400000	1.273192	0.348147
Bulgaria	0.430000	0.520000	0.470000	0.460000	0.551881	0.294735
Romania	0.500000	0.560000	0.560000	0.600000	0.321896	0.185401

a unique measure by which different shape of objects can be identify on the basis of their degree of fitness parameter. First, we have fitted a polygon/curve optimally on the object than compute the degree of fitness, which is a ratio of matching area and the non-matching area due to object and polygon/curve both. Next, we are identified the object of a particular geometrical shape (rectangle/circle/ellipse) on the basis of minimal value of degree of fitness for different fitted polygon/curve. We have tested the proposed general definition for identification of rectangular, circular and elliptical objects in various synthetic as well as real life data.

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REFERENCES

1. Nakagawa, Y. & Rosenfeld, A. A note on polygonal and elliptical approximation of mechanical parts. *Pattern Recognition*, 1997, **11**, 133-42.
2. Sychra, J.J.; Bartels, P.H.; Taylor, J.; Bibbo, M. & Weld, G.L. Cytoplasmic and nuclear shape analysis for computerised cell recognition. *Acta. Cytol.*, 1976, **20**, 68-78.
3. Zhu, C. & Wang, R. A fast automatic extraction algorithm of elliptic object groups from remote sensing images. *Pattern Recog. Let.*, 2004, **25**(13), 1471-478.
4. Zhang, S.C. & Liu, Z.Q. A robust real-time ellipse detector. *Pattern Recognition*, 2005. **38**(2), 273-87.
5. Horney, R.B.; Svalbe, I.D. & Wells, P. Isotropic subpixel measurement of circular objects. In the Proceedings of 7th Digital Image Computing: Techniques and Applications, edited by C. Sun, H. Talbot, S. Ourselin, and T. Adriansen, Sydney, 10-12, December 2003, 529-37.
6. Haralick, R.M. A measure of circularity of digital figures. *IEEE Trans. SMC*, 1974, **4**, 394-96.
7. Latecki, L.J.; Gross, A. & Melter, R. Shape representation and dissimilarity for image databases. *Pattern Recognition*, 2002, **35**(1), Special Issue.
8. Belongie, S.; Malik, J. & Puzicha, J. Shape matching and object recognition using shape contexts. *IEEE PAMI*, 2002, **24**, 509-22.
9. Grigorescu, C. & Petkov, N. Distance sets for shape filters and shape recognition. *IEEE Trans. Image Proc.*, 2003, **12**(10)1274-286.
10. Chaudhuri, D. & Samal, A. A simple method for fitting of bounding rectangle to closed regions. *Pattern Recognition*, 2007, **40**, 1981-989.
11. Chaudhuri, D. A simple object area based method for elliptic and circular fit of a two-tone image. *Def. Sci. J.*, 2008, **58**(6), 710-14.
12. Chaudhuri, D. A simple least squares method for fitting of ellipses and circles depends on border points of a two-tone image and their 3-D extensions. *Pattern Recog. Let.*, 2010, **31**, 818-29.
13. Swan, M. & Ridgway, J. Tools-math creating measures. www.wcer.wise.edu/archive/c11/flag/extra/download/tools, 2004. (Accessed on 22 November 2009)
14. Bollen, A.F.; Nguyen, H.X. & Dela Rue, B.T. Comparison of methods for estimating the bruise volume of apples. *J. Agri. Eng. Res.*, 1999, **74**, 325-30.
15. Lindsay, R.; Smith, G. & Atchison, D. Descriptors of corneal shape. *Optom Vision Sci.*, 1998, **75**, 156-58.
16. Skatter, S. & Hoibo, O. A. Cross sectional shape models of scots pine (*Pinus silvestris*) and Norway Spruce (*Picea abies*). *Holz als Roh-und Werkst*, 1998, **56**, 187-91.

17. Sun, Q. B.; Lam, C. P. & Wu, J.K. A practical automatic face recognition system. *In* H. Wechsler, 1998.
18. Soka, M.; Hlavac, V. & Boyle, R. Image processing, analysis and machine vision, International Thomson Publishing Company, New York, 1999.
19. Proffitt, D. The measurement of circularity and ellipticity on a digital grid. *Pattern Recognition*, 1982, **15(5)**, 383-87.
20. Peura, M. & Livarinen, J. Efficiency of simple shape descriptors. *In* Aspects of visual form processing, World Scientific, edited by C. Arcelli, L.P. Cordella, and G. Sanniti di Baja, Singapore, 1997, 443-51.
21. Rosin, P.L. Measuring rectangularity. *Machine Vis. Appl.*, 1999, **11**, 191-96.
22. Rosin, P.L. Measuring shape: ellipticity, rectangularity and triangularity. *Machine Vis. Appl.*, 2003, **14**, 171-84.
23. Flusser, J. & Suk, T. Pattern recognition by affine moment invariants. *Pattern recognition*, 1993, **26**, 167-74.
24. Chaudhuri, D. & Agrawal, A. A new split-and-merge segmentation technique by using bimodality detection approach. *Def. Sci. J.*, 2010, **60(3)**, 290-301.
25. Chaudhuri, D.; Kushwaha, N.K.; Sharif, I. & Samal, A. Bisection method for finding optimal rectangle based on area minimisation. *Machine Vis. Appl.*, 2011 (in press). Springer DOI-10.1007/s00138-011-0348-6.
26. Toussaint G.T. Solving geometric problems with the rotating calipers. *In* the Proceedings of IEEE MELECON '83, 1983, **A 10.02**, 1-4.
27. Nayak, A. & Stojmenovic, I. 2-D shape measures for computer vision. *In* Handbook of Applied Algorithms: Solving Scientific, Engineering, and Practical Problems. Wiley-IEEE Press, 2008, 347 -71.
28. Farin, G. Shape measures for triangles. *IEEE Trans. Visual. Comp. Graphics*, 2011, **18(1)**, 43-46.
29. Stojmenovic, M. & Nayak, A. Shape based circularity measures of planar point sets. *In* the Proceedings of the IEEE International Conference on Signal Processing and Communications (ICSPC 2007), 24-27 November 2007, Dubai, United Arab Emirates, 1279-282.
30. Zhang, J. & Wenyin, L. A pixel-level statistical structural descriptor for shape measure and recognition. *In* the Proceedings of the 10th International Conference on Digital Object (ICDAR '09), 2009, 386-90.
31. Stojmenovic, M. & Nayak, A. Direct ellipse fitting and measuring based on shape boundaries. PSIVT 2007, edited by D. Mery and L. Rueda, Springer-Verlag Berlin Heidelberg, LNCS **4872**, 2007, 221-35.

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