

Efficiency of Direction-Length Code (DLC) to Represent Binary Objects

Dr G D Jasmin

Assistant Professor, Loyola Academy Degree & PG College, Alwal, Secunderabad, India

ABSTRACT: As more information is digitized more and more digital images have been generated around the world. Efficient way of description and classification of objects is a well needed application to identify the objects that are present in images. Various methods have been developed for the representation aiming to effective classification of objects.

In this paper the Direction-Length Code also called a knowledge vector is generated to represent the shape of the objects. This vector gives the information of direction and length in every direction of the pixels of objects in the images. The Direction Length code (DLC) compresses the bi-level image, preserves the information at the same time allows a considerable amount of data reduction. These codes also can act as a standard input format for numerous shape-analysis algorithms. The efficiency of Direction Length Codes that is generated to describe the objects in the images is also examined in this paper.

KEYWORDS: Pre-processing, Object Description, Object Recognition.

I. INTRODUCTION

Object recognition in computer vision is the identification of objects present in the image via extraction of significant features or attributes. Various methods such as colour based representation, texture based representation, shape based representation and appearance based representation have been developed to represent objects. More studies on these methods are being carried out and advanced techniques are being developed. Shape is an important visual feature of objects in an image. Shape based representation of objects gives more clarity about the shape of the objects that acts as a more unique and important feature of objects for the further identification of objects. The encoding efficiency to represent shapes of objects is also very important for image storage and transmission [1].

The input image to the system may be a colour image, a gray scale image or a binary image. These images have to be converted to binary images for further processing. Segmentation is an important process in our object recognition system as it highlights the objects present in the image from its back ground. The contours are extracted from the image, the initial point is identified, the outline tracing algorithm is applied and the Direction-Length Code (DLC) is generated.

II. OVERVIEW OF OTHER SHAPE BASED METHODS

Various contour based shape description techniques such as simple shape descriptors, correspondence based shape matching, boundary moments, stochastic method, spectral transform and other structural methods such as chain code representation, polygon decomposition and shape invariants have been developed in the past [2-5]. A number of new techniques have been proposed in recent years [6,7,8,9].

Global contour shape techniques take the whole shape contour for the shape representation. The shape should be described as accurately as possible; on the other hand, a shape description should be as compact as possible to simplify indexing and retrieval. Simple global shape descriptors are compact, however, they are very inaccurate shape descriptors. They need to be combined with other shape descriptors to create accurate shape descriptors.

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Website: www.ijirset.com

Vol. 6, Issue 3, March 2017

Elastic matching and wavelet methods are complex to implement and match. Auto Regressive (AR) methods involve matrix operations which are expensive and it is difficult to associate AR descriptors with any physical meaning. Fourier descriptor (FD) is simple to implement, and involves less computation by either using fast Fourier transform (FFT) or using truncated Fourier transform computation. The resulting descriptor is also compact and the matching is very simple [10]. Compared with Curvature Scale Space (CSS) shape representation, FD is simpler to compute and more robust. Boundary moment descriptor is similar to Fourier descriptor, and is easy to acquire. However, unlike Fourier descriptor, only the few lower order moment descriptors have physical interpretation.

From a historical perspective there have been quite a few principled structural theories for shape perception. Chain-code techniques are widely used because they preserve information and allow considerable data reduction. Chain codes are used as the standard input format for numerous shape-analysis algorithms. The chain code usually has high dimensions and is sensitive to noise [11]. Iivarinen and Visa derived a chain code histogram (CCH) for object recognition [12]. The CCH reflects the probabilities of different directions present in a contour. The CHH is translation and scale invariant, however, it is only invariant to a rotation of 90°. Therefore, the normalized CHH (NCHH) is proposed. The NCHH reduces the dimensions of chain code representation, but does not solve the noise sensitivity problem.

Syntactic pattern recognition is inspired by the phenomenon that composition of a natural scene is an analogue to the composition of a language, that is, sentences are built up from phrases, phrases are built up from words and words are built up from alphabets, etc. The matching between shapes can use string matching by finding the minimal number of edit operations to convert one string into another. A more general method is to formulate the representation as a string grammar. Each primitive is interpreted as a alphabet of some grammar, where a grammar is a set of rules of syntax that govern the generation of sentences formed from symbols of the alphabet. The set of sentences generated by a grammar G is called its language and is denoted as $L(G)$. Here, sentences are strings of symbols (which in turn represent patterns), and languages correspond to pattern class. After grammars have been established, the matching is straightforward. For a sentence representing an unknown shape, the task is to decide in which language the shape represents a valid sentence. Syntactic shape analysis is based on the theory of formal language [13]. It attempts to simulate the structural and hierarchical nature of the human vision system.

III. DIRECTION LENGTH CODE (DLC) OF OBJECTS

The notion of 'Picture Description Languages' refers to the language of digital images defined over a regular array of vertices. Having extracted the contour of an image this process involves running through the contour pixel by pixel and finding the length of the contour in every possible direction.

The symbols used to represent the 8 possible directions - 2 horizontal, 2 vertical and 4 diagonal are R, DR, D, DL, L, UL, U and UR. Symbols R, D, L and U are elementary symbols and DR, DL, UL and UR are composite symbols of the alphabet. The directions denoted by these symbols are shown in Figure 1.

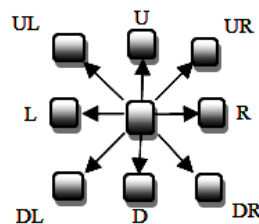


Figure 1: Direction Codes

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Website: www.ijirset.com

Vol. 6, Issue 3, March 2017

Let us consider an object S present in an image $f(x,y)$. A pixel p at coordinates (x,y) has 4 horizontal and vertical neighbours and 4 diagonal neighbours whose coordinates are given by $(x+1,y)$, $(x-1,y)$, $(x,y+1)$, $(x,y-1)$, $(x+1,y+1)$, $(x+1,y-1)$, $(x-1,y+1)$, $(x-1,y-1)$.

The connectivity between the pixels is an important concept used in the field of object recognition. If pixel p with coordinates (x,y) and pixel q with coordinates (s,t) are pixels of object S , a path from p to q is a sequence of distinct pixels with coordinates $(x_0, y_0), (x_1, y_1), \dots, (x_n, y_n)$, where $(x_0, y_0) = (x,y)$ and $(x_n, y_n) = (s,t)$, (x_i, y_i) is adjacent to (x_{i-1}, y_{i-1}) , $1 \leq i \leq n$, and n is the length of the path. If there a path exists from p to q consisting of pixels in S , then p is said to be connected to q . The gap of three or more pixels marks the presence of the next component in the same object or the beginning of the next object which can be then found by analysing the relationship among the components. Figure 3 shows the vector code generated for the square shaped object.

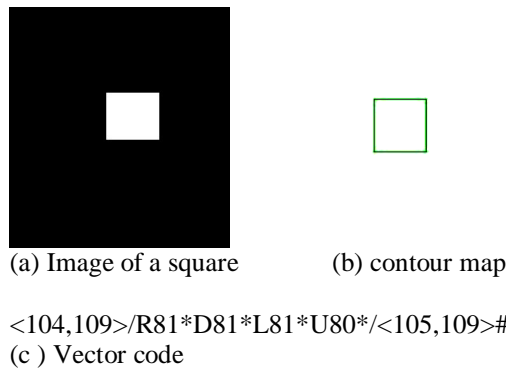


Figure 2: The DLC of a square

To reduce the complexity of the problem a gap filling algorithm is introduced to fill the small gaps present as noise in the image. A higher order pixel representation is considered as shown in figure 3.

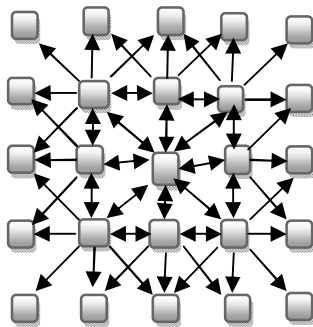


Figure 3: Higher order pixel representation

When the immediate neighbour of a pixel is not present, the algorithm looks for the pixels in the next level in the order of preferential directions. If pixels found in the next level, the algorithm connects the present pixel position to that in the next level to form connectivity thus filling the gap between pixels.

IV. GENERATION OF NORMALIZED KNOWLEDGE VECTOR

It is important to note that, when the diagonal lines appear in the image, they do not appear as the combination of only diagonal sides. The direction codes D and R appear with DR lines, D and L appear with DL, U and L appear with UL and U and R direction codes appear with UR.

Consider the image of a triangle and the corresponding vector code shown below.

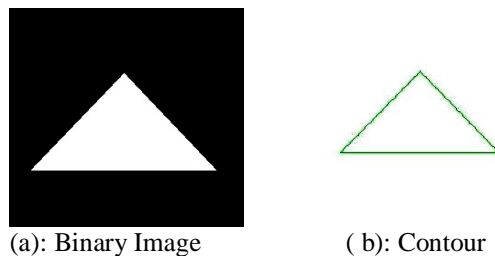


Figure 4: Image of a triangle

The DLC generated is

```
<75,121>/D1*DR2*D1*DR3*R1*DR1*D1*DR3*D1*DR3*D1*R7*D1*DR5*D1*DR2*D1*DR3*R1*DR2*D1*
DR1*D1*DR2*DR4*D2*DR2*R1*DR4*D2*DR7*D2*DR1*R1*DR5*D1*DR1*D1*DR8*D1*DR4*D1*DR3*D1*
DR3*R1*DR1*D1*DR3*D1*DR2*L175*UR3*U1*UR2*U1*UR2*R1*UR3*U1*UR2*U1*UR7*U1*UR7*U2*UR
5*R1*UR1*U1*UR2*U1*UR4*U1*UR7*U1*UR5*U1*UR1*U1*UR4*R1*UR3*U2*UR7*U2*UR1*R1*UR5*U1
*UR2*U1*UR4*U1*UR1*R1*UR2*U1*UR2*/<77,120>#
```

This is then reduced to single occurrence of eight directions as

```
<75,121>/R10*DR82*D23*L175*U21*UR82*/<77,120>#
```

An approximate measure taken such that when the amount of pixels in a particular direction is less than 10% of its total amount of pixels it need to be added to their corresponding major directions. This reduces the memory space needed as well as gives a clear idea about the shape of the object.

Thus the vector code obtained is

```
<75,121>/DR110*L175*UR108*/<77,120>#
```

and then normalized to 100 pixels as

```
→ DR28*L45*UR27
```

So, the final vector is a normalized vector called knowledge vector as it consists of more information of the object in its simpler form.

V. OBJECT CLASSIFICATION

The task of identifying regular shaped objects is simple. For the effective identification of irregular shaped objects, the shapes of the objects need to be approximated to some regular polygons to which it is closer to. This is done by predefining the regular shape classes and approximating the other shapes to fit into one of the predefined classes.

From the vector code generated it is observed that square consists of 4 basic directions with all lengths equal. Shapes with all the basic directions but with equal alternate length can be identified as a rectangle. Shapes with 4 sides consisting of only diagonal directions can be considered as rhombus.

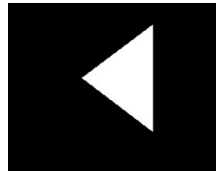
Let us now consider the triangle that is rotated by 90° to the left,

International Journal of Innovative Research in Science, Engineering and Technology

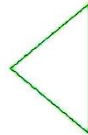
(An ISO 3297: 2007 Certified Organization)

Website: www.ijirset.com

Vol. 6, Issue 3, March 2017



(a) Image



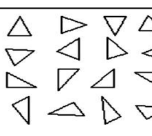





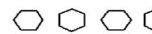
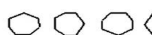
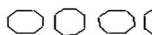

(b) Contour

Figure 5: Image of a rotated triangle and its contour

The knowledge vector limited to 8 directions is $\langle 34,170 \rangle / R15 * D184 * L16 * UL84 * U15 * UR84 * / \langle 35,169 \rangle \#$ and, the normalized vector is $\rightarrow D47 * UL27 * UR27$

It is observed that this vector code has 1 basic direction and 2 diagonal directions and can be classified as triangle.

Table 5: The classes of basic shapes with their vector codes

No	No of sides	Class	Shapes	Code	Precondition
1.	3 Sides	Triangle		DR-L-UR, R-DL-UL, DR-DL-U, D-UL-UR, R-DL-UL, D-UL-UR, DR-DL-U, DR-L-UR DR-L-U, R-DL-U, D-L-UR, R-D-UL, D-UL-UR, DR-L-UR, DR-DL-U, R-DL-UL	3 sides with 1 basic side and 2 diagonal sides or 3 sides with 2 basic side and 1 diagonal sides
2.	4 sides	Square		R-D-L-U, DR-DD-UL-UR, R-D-L-U, R-D-L-U, DR-DE-UL-UR	4 sides with all lengths equal
		Rectangle		R-D-L-U, DR-L-UL-U, R-DL-L-UR, DR-L-UL-U, R-DR-L-UL	4 sides with alternate lengths equal
		Parallelogram		R-DL-L-UR, DR-L-UL-U, R-DL-L-UR, DR-L-UL-U, R-DR-L-UL	4 sides with 2 basic sides and 2 diagonal sides DR and UL or DL and UR.
		Trapezoid		R-DL-L-UL, D-UL-U-UR, R-DR-L-UR, DR-D-DL-U, DR-L-UL-UR, R-DL-L-UL	4 sides with 2 basic sides and 2 diagonal sides DR and UR or DL and UL or DR and DL or UL and UR
3.	5 sides	Pentagon		DR-DL-L-UL-UR, DR-DE-UL-U-UR, R-DR-DL-UL-UR, DR-D-DL-UL-UR, R-DR-DL-L-UL-UR,	5 sides with 1 basic side and 4 diagonal sides
4.	6 sides	Hexagon		DR-D-DL-L-UL-U-UR, R-DR-DL-L-UL-U-UR, DR-D-DL-UL-U-UR, DR-D-DL-L-UL-U-UR, DR-D-DL-L-UL-U-UR,	6 sides with 2 basic sides and 4 diagonal sides
5.	7 sides	Heptagon		R-DR-DL-L-UL-U-UR, R-DR-D-DL-UL-U-UR, R-DR-D-DL-L-UL-U-UR	7 sides with 3 basic sides and 4 diagonal sides
6.	8 sides	Octagon		R-DR-D-DL-L-UL-U-UR, R-DR-D-DL-L-UL-U-UR, R-DR-D-DL-L-UL-U-UR, R-DR-D-DL-L-UL-U-UR,	8 sides with 4 basic sides and 4 diagonal sides
		Circle		DR-DE-UL-UR, R-DR-D-DL-L-UL-U-UR	4 diagonal sides or 8 sides with total pixels of basic sides < 25%

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Website: www.ijirset.com

Vol. 6, Issue 3, March 2017

Table 5 shows some of the classes of regular polygons with different variations, their corresponding vector code and their matching conditions.

VI. EFFICIENCY OF DLC ALGORITHM

The efficiency of the DLC representation of objects is analyzed and it is noted that the technique is rotation invariant, scale invariant, reduces the noise present in the form of pixel gaps minimizing the memory needed to store the image data.

6.1. Rotation Invariance

Rotation invariance is one of the major challenges to be taken care of during shape based recognition of objects. The representation of the object changes when rotated. This issue is well taken care of in this method by the precondition set to identify the shape of the objects that are all generalized rules.

6.2. Scale Invariance

The DLC vector is reduced to single occurrence of 8 directions and normalization is done in this method to make it suitable for various sized objects.

6.3. Pixel gap

The pixel gap present as noise in the contour of the object makes the system confused to identify the component as a part of the same object or as a component of another object. The unwanted small gaps between the pixels are filled using gap filling algorithm to make the object recognition easier.

6.4. Storage

The memory issues to store the DLC data of an image is taken into consideration. It is observed that the proposed algorithm reduces the memory space needed to store the image data. When compared with the space occupied by the contour of the original image the DLC data of the image occupies only half the space. It is been noted that the memory space occupied by the contour of the above image is 34.7 KB whereas the space needed to store the DLC code of that image is 16.8 KB thus reducing the space.

VII. CONCLUSION

In this paper we have reviewed various techniques available in the literature for the recognition of objects. The knowledge vector called Direction Length Code is generated for the description of objects. The performance of the system is analysed and it is noted that in some situations the system can perform object recognition very well even in the presence of noise. It also minimizes the need of storage at the same time preserving the information. The technique is effective, computationally inexpensive and can be applied to shapes with several variations.

REFERENCES

- [1] H. Freeman, "On the Encoding of Arbitrary Geometric Configurations," in Proceedings of IRE Translation Electron Computer, New York, pp. 260-268 (1961)
- [2] Zhang D, Lu G, "Evaluation of mpeg-7 shape descriptors against other shape descriptors", Multimedia Systems, 9(1) (2003)
- [3] Biederman, I., "Recognition-by-components: A theory of human image understanding", Psychological Review, 94: 115-147 (1987)
- [4] J.W. Mckee, J.K. Aggarwal, "Computer recognition of partial views of curved objects", IEEE Trans. Comput. C-26 790-800 (1977)
- [5] R. Chellappa, R. Bagdazian, "Fourier coding of image boundaries", IEEE Trans. Pattern Anal. Mach. Intell. 6 (1) 102-105 (1984)
- [6] Torralba, A., Oliva, A., Freeman, W. T., Object recognition by scene alignment [Abstract]. Journal of Vision, 3(9): 196, 196a (2003)
- [7] Leordeanu et al., "Beyond local appearance: Category recognition from pair wise interactions of simple features", IEEE Computer Society Conference on Computer Vision and Pattern Recognition (2007).
- [8] [Li Dong](#), Jiantao Zhou , [Yuan Y. Tang](#), "Noise Level Estimation for Natural Images Based on Scale-Invariant Kurtosis and Piecewise Stationarity", IEEE Transactions on Image Processing, [Volume: PP Issue: 99](#), Dec 2016.
- [9] [Tao Xi](#), [Wei Zhao](#), [Han Wang](#), [Weisi Lin](#), "[Salient object detection with spatiotemporal background priors for video](#)", IEEE Transactions on Image Processing, Page(s): 1, Nov 2016.
- [10] C.W. Richard, H. Hemami, "Identification of three dimensional objects using Fourier descriptors of the boundary curve", IEEE Trans. System Man Cybernet, SMC-4 (4) 371-378 (1974).
- [11] D. Zhang, G. Lu , "Review of shape representation and description techniques", Pattern Recognition 37 : 1-19 (2004)
- [12] J. Iivarinen, A. Visa , "Shape recognition of irregular objects", Intelligent Robots and Computer Vision XV: Algorithms, Techniques, Active Vision, and Materials Handling, Proc. SPIE 2904 25-32 (1996).
- [13] K.S. Fu, "Syntactic Methods in Pattern Recognition", Academic Press, New York (1974).