KERNEL-BASED OBJECT DETECTION

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Abstract— This paper describes the detecting object based on kernels. Objects are detected by background differencing. Low contrast levels can present problems, leading to poor object segmentation and fragmentation, particularly on older analogue tracking system. The object detection can be done through the kernel, which is interacting with the given image by morphology and result will be identified. The model-free tracking or detecting algorithm described in this paper addresses object fragmentation and the masking induces spatially-smooth similarity. The morphological operators are applied with kernel for detecting the specific objects.

1 INTRODUCTION

Morphological based object detection with in image is difficult task. One way to simplify the problem is to change the grayscale image into a binary image, in which each pixel is restricted to a value of either 0 or 1. The techniques used on these binary images go by such names as: blob analysis, connectivity analysis, and morphological image processing. The foundation of morphological processing is in the mathematically rigorous field of *set theory*; however, this level of sophistication is seldom needed.

1.1. Mathematical Representation of Morphological Processes

Most of the mathematical formalism and notations are adopted from Serra (1982). To understand procedure, certain basic mathematical morphological transformations are detailed along with list of symbols and notations. Mathematical morphology based on set theoretic concepts is a particular approach to the analysis of geometric properties of different structures. The main objective is to study the geometrical properties of a natural feature represented as a binary image by investigating its microstructures by means of "kernels", following Serra's concept (1982). It aims to extract information about the geometrical structure of an object by mathematical morphological concepts. In this, specific object detection features are subjected to transformations by means of another object called kernel. The main characteristics of kernels are, shape, size, origin and orientation. Different kernels can characterize the topological characteristics spatial distribution. According to Matheron's (1975) approach, each image object is assumed to contain its boundary, and thus can be represented by a closed subset of Euclidean space. In addition many kernels are represented by a compact subset of E, so that constraints which correspond to the four principles of the theory of mathematical morphology such as invariance under translation, compatibility with change of scale, local knowledge and upper semi-continuity will be imposed on morphological set transformations (erosion, dilation, opening and closing).

Dilation, *erosion*, *opening* and *closing* are simplest quantitative morphological set transformations. These transformations are based on Minkowski set addition and subtraction. The Minkowski set addition of two sets, *M* and *S*, is shown in Eq. (1).

$$M \oplus S = \{m + s : m \in M, s \in S\} = \bigcup_{s \in S} M_s \qquad (1)$$

M and *S* consist of all points *c* which can be expressed as an algebraic vector addition $c = m+s$, where the vectors *m* and *s* respectively belong to *M* and *S*.

The Minkowski set subtraction of *S* from *M* is denoted as

$$M \ominus S = (M^c \oplus S)^c = \bigcap_{s \in S} M_s \qquad (2)$$

Let *M* be a binary image where the pixels with 0s are marked with a dot for a better legibility. Kernel *S* will be moved from top to bottom and left to right by applying the criterion of erosion principle to achieve shrinking. When the rectangle, *S* is centered on one point of the frame of the image *M*, then it will be truncated and only its intersection with the shape is kept.

The discrete binary image, *M*, is defined as a finite subset of Euclidean 2-dimensional space, R^2. The geometrical properties of a binary image possessing set (*M*) and set complement (M^c) are subjected to the morphological functions. From geometrical point of view morphological dilations and erosions are defined as set transformations that expand and contract a set. The morphological operators can be visualized as working with two images. Each kernel has a designed shape that can be thought of as a probe of the main feature. The three morphological transformations involved in this study are dilation to expand erosion to shrink, and cascade of erosion-dilation to smoothen the set.

Dilation : Dilation combines two sets using vector addition of set elements. If *M* and *S* are sets in Euclidean space with elements *m* and *s*, respectively, $m = (m_1, \ldots, m_N)$ and $s = (s_1, \ldots, s_N)$ being *N* -tuples of element co-ordinates, then the dilation of *M* by *S* is the set of all possible vector sums of pairs of elements, one coming from *M* and the other from *S*. The dilation of a set, *M*, with kernel, *S* is defined as the set of all points such that S_m intersects *M*. It is worth mentioning here that Minkowski addition and subtraction are akin to the morphological dilation and erosion as long as the kernel(*S*) is of symmetric type. As long as the kernels are symmetric ($S = \hat{S}$) Minkowski's addition and subtraction are respectively similar to morphological dilation and erosion.

$$M \oplus \hat{S} = \left\{ m : S_m \bigcap M \neq \varnothing \right\} = \bigcup_{s \in S} M_{-s} \qquad (3)$$

This operation enlarges the objects and neighboring particles will be connected.

Erosion: The erosion of an image, *M*, with kernel, *S* is defined as the set of points *m* such that the translated S_S is contained in *M*. It is expressed as:

$$M \ominus \hat{S} = \left\{ m : S_m \subseteq M \right\} = \bigcap_{s \in S} M_{-s} \qquad (4)$$

where -*S* = {-*s: sS*}, i.e., *S* rotated 180^{o} round the origin.

1.2. Theory of kernels

Kernel is a microstructure of the set with which transformations are to be performed. Broadly these structuring elements are categorized as symmetric and asymmetric types. Moreover, 1-D and 2-D structuring elements can also be defined at will. The role of structuring element is to unravel the hidden morphological properties of the set that is transformed by structuring element according to a particular rule. This functions as an interface between objective and subjective.

1.3. Property of iteration

To generate a large size erosion or dilation, the dilation as well as erosion can be iterated. Instead of using a larger structuring element, with the use of smaller structuring element repeatedly one will get the same effect, although not all dilations with a large structuring element can be so decomposed. is the symbol for the dilation. Carrying out dilation twice is represented as

$$\begin{matrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{matrix} \quad \oplus \quad \begin{matrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{matrix} \quad = \left| \begin{matrix} 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \end{matrix} \right.$$

Fig 1 Dilation by 3x3 kernel

The above diagrammatic representation is represented as the following mathematical notation.

$$S \oplus S \oplus S \oplus \ldots \oplus S = S_n \qquad (5)$$

Decomposition of structuring elements: Several other structuring elements include circle, segment, bi-points, triangle. Moreover, these structuring elements can be defined at will to unravel hidden properties of image under investigation. This choice is based on the type of result to get the purpose of the transformation. The transpose of kernel is shown in Fig. 2.

$$\begin{array}{ccccc} 1 & 1 & 1 & 1 & 1 \\ & 1 & 1 & 1 & \\ & & 1 & & \end{array} \qquad \begin{array}{ccccc} & & 1 & & \\ & 1 & 1 & 1 & \\ 1 & 1 & 1 & 1 & 1 \end{array}$$

$$\boldsymbol{S} \qquad\qquad\qquad \hat{S}$$

Fig. 2 The triangular kernel and its transpose

S_x will be the kernel centered in x and S, the symmetric of S relative to its center. S_h will be translated set by vector h- as shown in Fig. 2. Prior to understand the impact of other types of kernel on the structure it should be noted that there are several types of line kernel or 1-D kernel. Following are the line kernel with direction 0^0, 45^0, 90^0, 135^0, 180^0, 225^0, 270^0, and 315^0 that are available on a square grid, and 0^0, 60^0, 120^0, 180^0, 240^0, and 300^o are on hexagonal grid.

$$\begin{array}{c} 1 \\ 1 \\ 1 \end{array} \qquad \begin{array}{ccc} & & 1 \\ & 1 & \\ 1 & & \end{array} \qquad \begin{array}{ccc} 1 & 1 & 1 \end{array} \qquad \begin{array}{ccc} 1 & & \\ & 1 & \\ & & 1 \end{array}$$

Fig. 3 The line kernel and its transpose

These 1-D kernels can be used to shrink or expand the size of the objects in the given direction and may discard them. These line-kernels are centered on the right side for the erosion, and on the left side for the dilation. Many other objects can be generated as shown in the following representations with the 1-D kernels.

$$\begin{array}{ccc} & & 1 \\ & 1 & \\ 1 & & \end{array} \oplus \begin{array}{ccc} 1 & & \\ & 1 & \\ & & 1 \end{array} = \begin{array}{ccc} & 1 & \\ 1 & 1 & 1 \\ & 1 & \end{array}$$

$$\begin{array}{ccc} & & 1 \\ & 1 & \\ 1 & & \end{array} \oplus \begin{array}{ccc} 1 & 1 & 1 \end{array} \oplus \begin{array}{ccc} 1 & & \\ & 1 & \\ & & 1 \end{array} = \begin{array}{ccccc} & 1 & 1 & 1 & \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ & 1 & 1 & 1 & \end{array}$$

Fig. 4 The Object generation with 1-D kernels

1.3. Multi-scale operations

As already mentioned, the simplest morphological set transformations are *erosion*, *dilation*, *opening* and *closing*. Since, the structuring element is of symmetric type both Minkowski's subtraction and addition are similar to morphological erosion and morphological dilation respectively (Sagar 1996, Sagar *et al*. 1998a, 1998b). The dilation followed by erosion is called closing transformation. Cascade of erosion-dilation is called opening transformation. These cascade transformations are idempotent (Serra 1982). However, these transformations can be carried out according to the multiscale approach (Sagar *et al*. 2000). In the multiscale approach, the size of the structuring template will be increased from iteration to iteration. The opening and closing operations are *idempotent*; i.e., $\{[(M\oplus S) \oplus S] \oplus S\} \oplus S = (M\oplus S) \oplus S$, and similarly closing (Serra 1982, Sagar *et al*. 2000, 2003). But a variation will be identified while performing either opening or closing as multiscale operations/cycles, i.e.,

$$\{[(M\oplus S) \oplus S] \oplus S\} \oplus S = (M\oplus S_2) \oplus S_2 \qquad (6)$$

Theoretically, the above expression is true. Other way of performing opening is the right side notation. In this subsection opening and closing operations are performed on the basis of cycles. As shown in Eq. (5), the size of structuring element will be changed as follows; if S is of size 3 x 3 pixels, this means that instead of using a larger structuring element, it is often possible to use a smaller one repeatedly to get the same effect.

The diagrammatic representation is shown as square type of structuring element of two sizes and the cumulative effect through addition. According to the expression (6), two consecutive erosions and dilations can be respectively represented as

$$(M\ominus S)\ominus S = M\ominus S_2, \text{ and } (M\oplus S) \oplus S = M\oplus S_2 \qquad (7)$$

The transformations from the field of mathematical morphology such as *erosion,* *dilation,* and *opening* discussed so far are used to extract morphological skeletal network (*MSN*).

Segmentation is to distinguish objects from background [8]. For intensity images (ie, those represented by point-wise intensity levels) four popular approaches are: threshold techniques, edge-based methods, region-based techniques, and connectivity-preserving relaxation methods. Threshold techniques, which make decisions based on local pixel information, are effective when the intensity levels of the objects fall squarely outside the range of levels in the background. Because spatial information is ignored, however, blurred region boundaries can create havoc.

2. Model-based Recognition

In model-based recognition problems, a model of an object undergoes some geometric transformation that maps the model into a sensor coordinate system (say, an image plane or a cylindrical coordinate system from a 3D scanner). The development of efficient algorithms for identifying such transformations is central to many model-based recognition systems.

There are a number of other approaches to model-based recognition which employ non-trivial geometric algorithms, and which often draw explicitly on results from computational geometry. The affine hashing method (Lamdan and Wolfson 1988) uses a redundant representation of a set of points in order to locate that point set under an affine transformation, in the presence of extraneous data points. The underlying idea is to use each triple of points in the model as an affine basis, and rewrite the other model points in terms of each basis. In order to recognize an object, triples of image points are selected, and for each triple all remaining image points are expressed in terms of the basis. When a correct basis is found, this will result in affine invariant coordinates that are the same (up to sensing error) as one of the encodings of the model.

Several researchers have developed recognition methods that explicitly account for sensor errors. These methods make considerable use of results on arrangements from computational geometry. Most of these methods represent each point or line segment in an “image" set as a polygonal region (say, the Minkowski sum of the image set with a box). The matching problem is then to search for transformations bringing each point or line segment of the model into such a polygonal region in the image. These problems can be structured as sweeping arrangements, using algorithms from computational geometry (Atherton *et al.* 1987, Baird 1985). A different approach to model-based matching problems involves the development of cost functions for measuring the difference between two sets of points and line segments under various transformations. The applied methods developed in the vision community are provably good approximation schemes for solving the combinatorial problems that were originally investigated in the computational geometry community.

2.1. Kernel Based object detection

The detection of an object from the scene is the main purpose of this paper. Binary image has been identified from the given image and then try to apply the morphological operators on it. When we introduce the morphological operations it tries to remove the noise and give the objects based on the kernels. We try to use several kernels like square, rectangle, circle, octagon, triangle and ramous. Any object which is in binary, *opened* with the particular kernel will produce the same kernel after n-1 iterations, so the kernels are playing main role on the object which is used. The kernels are influenced in the object and try to act, which helps to identify the real one.

This procedure includes systematic use of multi-scale opening and simple logical operators. The multi-scale openings and closings are useful smoothing filters because they preserve the shape and location of vertical abrupt signal discontinuities; further, the definition of scale in the openings is identical to the spatial size of geometrical objects. When we use multi-scale openings in the image with kernels, the resultant object is look like the kernel after n-1 times. If we exceed one more openings, the image will be vanished, because the kernel and n-1 time opened image is same, by using this approach, it is vary compact to identify the object based on kernels. In our examples we try to use only few kernels but it is also possible to use more kernels, which will give more specific aspects of object detection based on kernels.

The procedure has some specific limitation, which is only applied in binary image and related to identify the object based on the kernels. Some of the noise also removed when we having this systematic approaches.

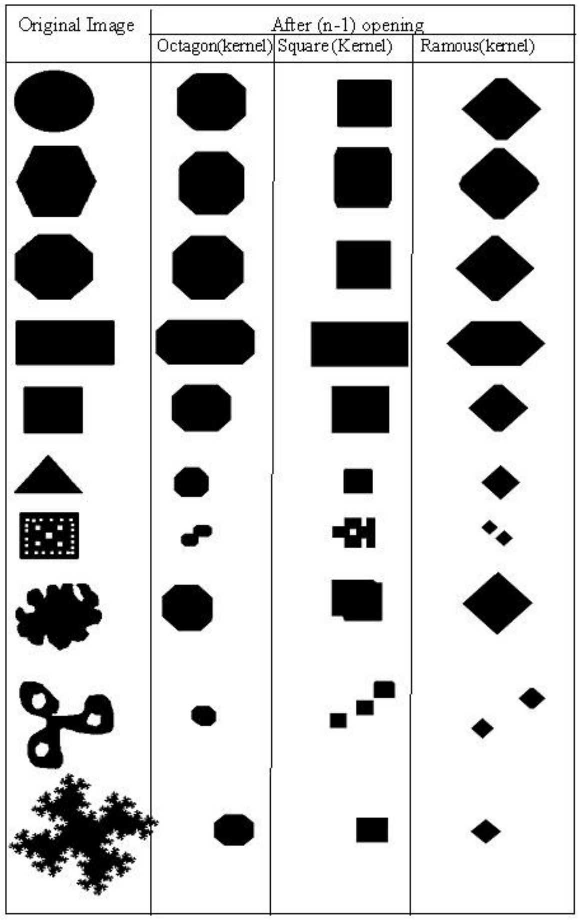

Fig: 5. Comparison table of the original image with n-1 opening of the same image with different kernels.

The above table shows how the kernels have influence on the binary images based on the kernels. This simple study gives object detection approach for the input image and based on the kernel which we applied on it. So the kernels are deciding the morphological opening on the binary image. For better understanding we have some discussion on object detection using different examples based on kernels. The following figure is simple image which has different object, by using our approach we try to detection ramous based object or line based object or circle based object. This is possible by applying the morphological opening in the image based on line kernels or ramous kernels or octagon kernels. After applying k times some of the noises are removed and n-1 times the specific objects are detected based on kernels. Usually the noises are smaller in size so when we use the minimum number of opening on the image, it disappears. But the object detection is possible until we do for n-1 times.

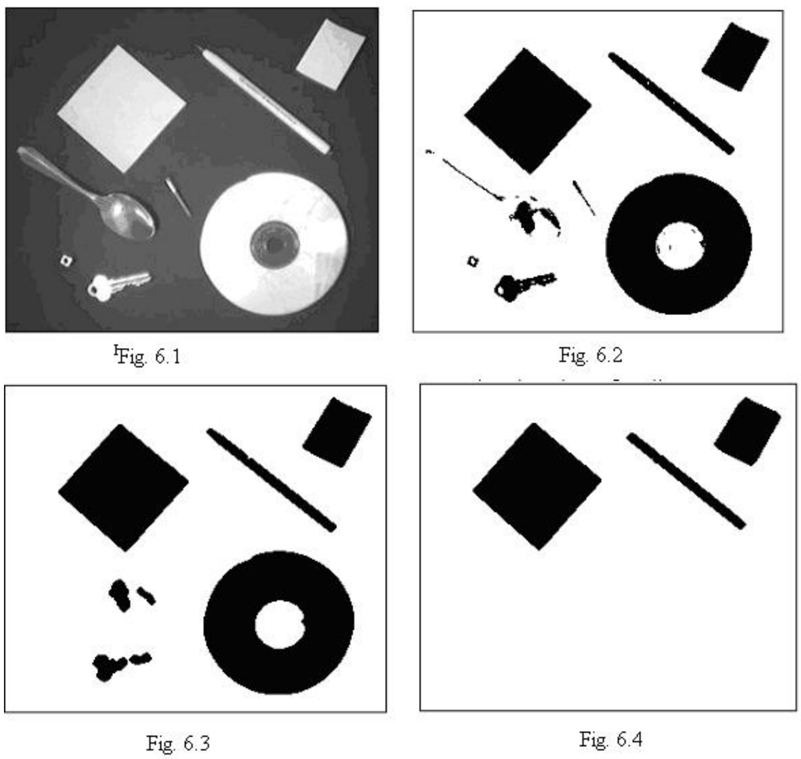

Fig. 6: (6.1) the image for object detection, (6.2) tThe Binary image, (6.3) after Appling *open* k times in the binary image, and (6.4) After Appling *open* n-1 times in the binary image with rhombus kernel.

For more specification, we try to consider some examples like Micrograph of brain cells containing a Lewy body, which is the light purple sphere near the center of the image. (Kondi Wong, Armed Forces Institute of Pathology, July 1, 2004) and The *Trichinella* roundworm as it appears within human muscle (Centers for Disease Control and Prevention (CDC)). These are above example will give some specific detection on the original like brain cells or roundworm based on kernels which applied on the original binary image.

Initially, we converted the image into binary and then apply the morphological opening on it based on different kernels, which yield the different kind of object detection. So the detection of an object from an image by applying morphological openings as a approach for detection any specific objects related to kernel is possible on the binary image.

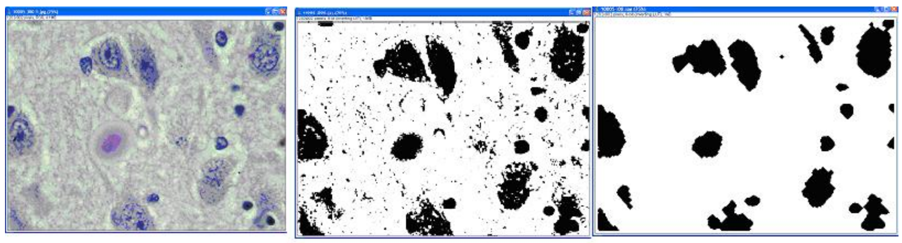

Fig. 7.1 Fig. 7.2 Fig. 7.3

Fig. 7: (7.1) micrograph of brain cells containing a Lewy body, (Kondi Wong, Armed Forces Institute of Pathology, July 1, 2004), (7.2) the binary form of micrograph, and (7.3) brian cells detection based on morphological openings.

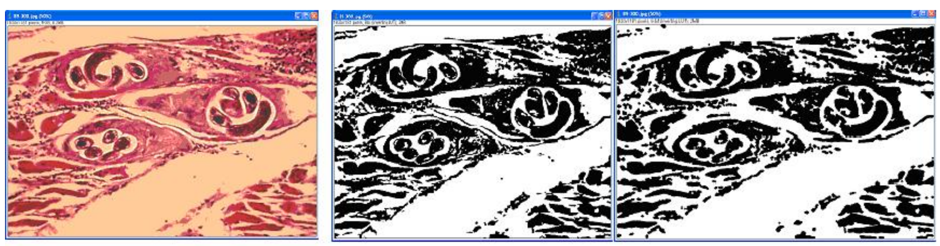

Fig. 8.1 Fig. 8.2 Fig. 8.3

Fig. 8: (8.1) the *Trichinella* roundworm as it appears within human muscle, (8.2) the binary form of human muscle, and (8.3) the roundworm detection from human muscle image.

3. CONCLUSION

The basic images are producing simple results based on the kernel which is applied on it. But the real application on the human muscles or brain cells has some limitations. The kernels which we use in the image has some different results for morphological openings, however this approach need to have some more improvement for any other applications. Object detection has lot of application like using CCTV camera objects and try to identify the person who enters into a specific shop or house based on kernels. The approach may help to detect the object which is captured from CCTV camera.

REFERENCE

1. J. Serra, Image Analysis and mathematical morphology (Academic press, New York) 1982, p. 610.
2. Matheron, G. (1975) Random Sets and Integrated Geometry Wiley: New York.
3. Sagar, B. S. D. (1996) Fractal relations of a morphological skeleton, Chaos, Solitons & Fractals, 7(11), 1871-1879.
4. Sagar.B.S.D, Venu.M, Gandhi.G, Srinivas.D, (1998a), "Morphological description and interrelation between force and structure: a scope to geomorphic evolution process modeling", International Journal of remote sensing, 19 (7) ,1341-1358.
5. Sagar, B. S. D., Omoregie, C., & Rao, B. S. P. (1998b) Morphometric relations of fractal-skeletal based channel network model Discerte Dynamic Nature Society. 2(2),77-92.
6. Sagar.B.S.D, Venu.M and Srinivas.D, (2000), "Morphological operators to extract channel networks from Digital Elevation Models", International Journal of Remote Sensing, 21(1), 21-30.
7. Sagar, B. S. D., Murthy, M. B. R., Rao, C. B., & Raj, B. (2003) Morphological approach to extract ridge-valley connectivity networks from Digital Elevation Models (DEMs) Int. J. Rem. Sens. 24(3), 573 – 581.
8. Asano, T., Chen, D.Z., Katoh, N., Tokuyama, T. *Polynomial-time solutions to image segmentation*, Proc. of the 7th Ann. SIAM-ACM Conference on Discrete Algorithms (Jan. 1996), 104-113.
9. Lamdan, Y., Wolfson, H.J. *Geometric hashing: A general and efficient model-based recognition scheme*, International Conference on Computer Vision (1988), 238-249.
10. Atherton, P., Earl, C., Fred, C. *A graphical simulation system for dynamic five-axis NC verification*, Autofact Show of the Society of Manufacturing Engineers, Detroit, Nov. 1987, 2-1 - 2-12.
11. Baird, H.S. *Mode-Based Image Matching Using Location*, MIT Press, 1985.