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VLSI IMPLEMENTATION OF ROBUST CIRCLE DETECTION ON IMAGE USING GENETIC OPTIMIZATION TECHNIQUE

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ABSTRACT

Hough transform is used for detecting circles in an image. To reduce the huge computations in Hough transform, a resource efficient architecture is essential. Resource efficient and reduction in processing time are achieved with data parallelism. we present a circle detection method based on genetic algorithms. Our genetic algorithm uses the encoding of three edge points as the chromosome of candidate circles (x,y,r) in the edge image of the scene. Fitness function evaluates if these candidate circles are really present in the edge image. Our encoding scheme reduces the search space by avoiding trying unfeasible individuals, this result in a fast circle detector. The implementation of GA-based Hough transform on an FPGA. This architecture is implemented using altera device at operating frequency of 200MHz. It compute the Hough transform of 512x512 test images with 180 orientation in 2.05 to 3.15ms with minimum number of FPGA resources

Keywords – Matlab, edge detection, circle detection, Genetic algorithm, Robustness, circleobject recognition.

1. INTRODUCTION

One on the most challenging tasks in Computer Vision is feature extraction in images. Usually objects of interest may come in different sizes and shapes, not pre-defined in an arbitrary object detection program. A solution to this problem is to provide an algorithm than can be used to find any shape within an image then classify the objects accordingly to parameters needed to describe the shapes. The problem of detecting circular features arises inside many areas of image analysis, being particularly relevant for some industrial applications such as automatic inspection of manufactured products and components, aided vectorization of drawings and target detection among others [1]. Two sorts of techniques are commonly applied to solve the object location challenge: first hand deterministic techniques including the application of Hough transform based methods [2], geometric hashing and template or model matching techniques[3, 4]. On the other hand, stochastic techniques including random sample consensus techniques [5], simulated annealing [6] have been also used. Two problems are major concern here: either the objects searched for are difficult to distinguish or the detection is to be performed in real time. The first problem is due to non-even illumination, low-contrast, noise or restricted, partial visibility of objects.

In our work, we present a GA-based circle detector. Our system uses a three edge point circle representation that lets the system to reduce the search space by eliminating unfeasible circle locations in our image. This approach results in a sub-pixellic circle detector that can detect circles in real images even when the circular object has a significant occluded portion. We present the results of the application of our method to synthetic images, real-world images and Hand- drawn circles.

2. RELATED WORK

Template and model matching techniques were the first approaches to shape detection. Shape coding techniques and combination of shape properties were used to represent objects. Plenty of methods have been developed to solve the shape detection problem (Peura and Iivarinen, 1997). Main drawback of these techniques is related to the contour extraction step from real images.

The Hough Transform. Invented by Richard Duda and Peter Hart in 1992, the HT was originally meant to detect arbitrary shapes of for different objects. The Hough Transform was later extended to only identify circular objects in low-contrast noisy images, often referred to as Circular Hough Transform. Circle detection in digital images is commonly performed by the Circular Hough Transform [9].

A typical Hough-based approach employs edge information obtained by means of an edge detector to infer locations and radius values. Peak detection is then performed by averaging, filtering and histo-gramming the transformed space. However, such an approach requires a large storage space given the required 3-D cells to cover all parameters (x, y, r) and a high computational complexity which yields a low processing speed. The accuracy of the extracted parameters for the detected circle is poor, particularly under the presence of noise [3]. For a digital image holding a significant width and height and a densely populated edge pixel map, the required processing time for Circular Hough Transform makes it prohibitive to be deployed in real time applications.

In order to overcome this problem, some other researchers have proposed new approaches based on the Hough transform, for instance the probabilistic Hough transform [11], the randomized Hough transform (RHT) [12] and the fuzzy Hough transform [13]. Alternative transformations have also been presented in literature as the one proposed by Becker in [14]. Although those new approaches demonstrated faster processing speeds in comparison to the original Hough Transform, they are still highly sensitive to noise [10].

3. CIRCLE DETECTION USING GA

(A)Genetic Operation

In its simplest form, a genetic algorithm consists of three mechanisms: (i) parent selection, (ii) genetic operation for the production of descendants (offspring), and (iii) replacement of parents by their descendants, [2]. Parent selection process follows one of the selection processes of roulette, classification, constant situation, proportional forms or elitist choice. The genetic operations of (i) crossover and (ii) mutation combine parents to produce offspring of improved characteristics (getting higher grade by the evaluation function). Parent replacement strategies include (i) generational replacement and (ii) steady state reproduction.

For the selection operator we have used a roulette wheel implementation. In this method, each individual is assigned a slice in the roulette wheel. The size of the slice is proportional to its normalized fitness value. This selection strategy favors best fitted individuals but it gives a chance to the less fitted individuals to survive. A steady state policy is also used, this implies to have elite individuals that will be kept in the next population.

For the crossover operator, we have used a 1-point crossover implementation. This method uses a crossover probability value to determine where we will divide the genetic material of the two parents to recombine into a new individual. A bit mutation operator is used in our implementation. In this method, a bit is inverted or not depending on a mutation probability.

(B)Solution Formation

We represent circles by using the parameters of the second degree equation passing through three edge points in the edge space of the image. Images are preprocessed by using an edge detection step. We store locations for all the edge points. The detected edge points are the only potential candidates to define circles in our image, taken in triplets. We need an edge detection method that obtains a single pixel contour for objects in the image. We have used a canny edge detector as implemented. All the edge points in the image are stored in a vector array V (v_0; v_1; . . . ; v_n) with N the total number of edge points in the image .We store the (x_i,y_i) coordinates for each edge pixel vi in the edge vector.

We encode each individual as the concatenation of the binary codes of the indexes i_1, i_2 and i_3 of three edge points. We consider the circle passing through the points v_{i1} ; v_{i2} ; v_{i3} as a potential solution to the detection of circles in images. A number of these candidate solutions are generated for the initial population of the GA. We evolve this solution by using genetic operators in the simple GA approach. When a given threshold is obtained in the fitness evolution of the population, best individual is taken as the solution of the circle detection problem.

(C) *Individual Solution*

Each individual C uses three edge points as chromosomes. In this representation, edge points are stored as an index to their relative position in the edge array V of the image. That will encode an individual as the circle that passes through the three points v_i, v_j and v_k. We represent each circle C by the three parameters x_0, y_0 and r. With (x_0,y_0) being the (x,y) coordinates of the center of the circle and r being its radius. We can compute the equation of the circle passing through the three edge points as:

$$(x-x_0)^2 + (y-y_0)^2 = r^2$$

$$x_0 = \frac{\begin{vmatrix} x_j^2+y_j^2-(x_i^2+y_j^2) & 2(y_j-y_i) \\ x_k^2+y_k^2-(x_i^2+y_i^2) & 2(y_k-y_i) \end{vmatrix}}{4\left((x_j-x_i)(y_k-y_i)-(x_k-x_i)(y_j-y_i)\right)}$$

$$y_0 = \frac{\begin{vmatrix} 2(x_j - x_i) & x_j^2 + y_j^2 - (x_i^2 + y_i^2) \\ 2(x_k - x_i) & x_k^2 + y_k^2 - (x_i^2 + y_i^2) \end{vmatrix}}{4((x_j - x_i)(y_k - y_i) - (x_k - x_i)(y_j - y_i))}$$

$$r = \sqrt{(x - x_0)^2 + (y - y_0)^2}$$

previous computations for x0, y0 and r. Using the indexes as computational chromosomes, we can sweep a continuous space for the shape parameters but keeping a binary string representation of the GA individual. This approach reduces the search space by eliminating unfeasible solutions.

(D)*Fitness evaluation*

In order to compute the fitness value of an individual C, we compute the coordinates of the edge points in a virtual sampled shape.We then validate if they actually exist in the feature space. The test set for these points is S $\{s_1, s_2, \ldots s_n\}$ with Ns, the number of test points where the existence of an edge border will be seek. The test point set S is generated by the uniform sampling of the shape boundary. In our case, Ns test points are generated around the circumference of the candidate circle. Each point s_i is a 2D-point where its coordinates (x_i,y_i) are computed as follows:

$$x_i = x_0 + r \cdot \cos\frac{2\pi i}{N_s}$$

$$x_i = x_0 + r \cdot \sin\frac{2\pi i}{N_s}$$

Fitness function F(C) accumulates the number of expected edge points (i.e. the points in the set S) that actually are present in the edge image. That is:

$$F(c) = \frac{\sum_{i=0}^{N_s - 1} E(x_i, y_i)}{N_s}$$

with $E(x_i,y_i)$ being the evaluation of edge features in the image coordinate (xi,yi) and Ns being the number of pixels in the perimeter of the circle corresponding to the individual C under test. As the perimeter is a function of the radius, this serves as a normalization function with respect to the radius. That is, F(C) measures completeness of the candidate circle encoded by the computational chromosome. Our objective is then to maximize F(C) because a larger value implies a better response to this circularity operator. We can stop the optimization process by fixing a number of epochs to evolve the chromosomes or by satisfying a completeness threshold. Each of these procedures implies some a priori knowledge about the specific application context of the circle detector. In our tests, we have fixed a number of epochs for population evolution.

We can then represent the shape parameters (for the circle, $[x_0,y_0, r]$) as a transformation T of the edge vector indexes i,j, k. with T being the

4. EXPERIMENT AND RESULT

The experimental setup includes the use of iris images of 512 x 512 pixels. Parameters of interest are the (x,y) center of the circle position and its radius We have generated randomly located circle in them. The algorithm has been run 10 times for each test image. We can say that the average error for localization is 0.06 pixels and the worst case (maximum error) is 0.31 pixels. That is, the proposed algorithm finds the circle parameters in a sub-pixel level and with an error lower than a tenth of pixel. The detection is robust to translation and scale and the elapsed time is reasonably low (typically under 153 ms).

5. RESULT AND COMPARISION

Fig:1Input image

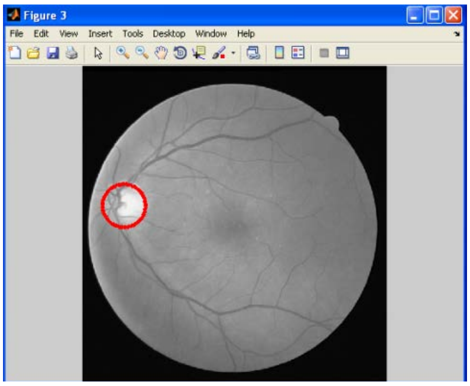

Fig:2 Circle detection output

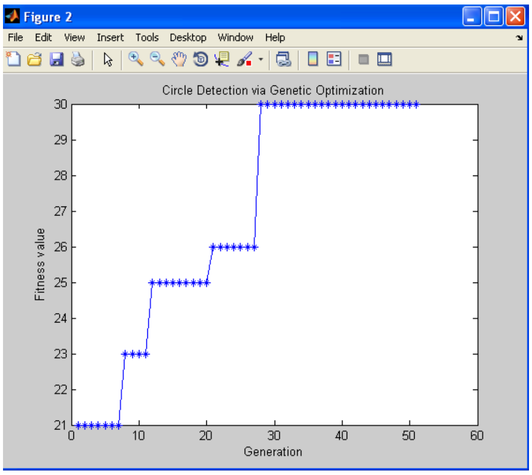

Fig:3 Circle Detection via Genetic Optimitation

6. CONCLUSION

In this paper, we have presented a GA-based circle detector. Our system is capable of detecting circles with sub-pixellic accuracy in synthetic images. We can also detect circles in real-world images with sub-pixellic precision. The encoding scheme used in this method encodes circles by using the equation for the ideal circle passing through three edge points. The search space is reduced because we only try the circles that can pass through the actual edge points in the scene. This results in a fast detector as compared to recent results in literature. Our circle detector can reliably detect circles even if they present significative occlusions, discontinuities or incompleteness. The result shows that the proposed PE could achieve the best throughput with the same amount of resources compared to previously reported architectures. The proposed PE is implemented on an Alter a kit device and the maximum frequency is 200 MHz .

REFERENCES

[1] Roth, G. and Levine, M. D.: Geometric primitive extraction using a genetic algorithm. *IEEE Trans. Pattern Anal. Machine Intell*. 16 (9), 901–905, 1994.

[2] Lam, W., Yuen, S.: Efficient techniques for circle detection using hypothesis filtering and Hough transform. *IEEE Proc. Visual Image Signal Process.* 143 (5), 292–300, 1996.

[3] T.J. Atherton, D.J. Kerbyson, Using phase to represent radius in the coherent circle Hough transform, in: Proceedings of the IEEE Colloquium on the Hough Transform, IEEE, London, 1993.

[4] V. Ayala-Ramirez, C.H. Garcia-Capulin, A. Perez-Garcia, R.E. Sanchez-Yanez, Circle detection on images using genetic algorithms, Pattern Recognition Letters 27 (2006) 652–657.

[5] Canny, J., A Computational Approach to Edge Detection, IEEE Trans. Pattern Analysis and Machine Intelligence, 8, 679-714, 1986.

[6] Lutton, E. & Martinez, P. (1992). A Genetic algorithm for detection of 2D geometric primitives in images. Proc. of the IEEE Int. Conf. on Pattern Recognition (ICPR), (1) pp. 526-528.

[7] B. _Ilker, S. Birbil, F. Shu-Cherng, R.L. Sheu, On the convergence of a population-based global optimization algorithm, Journal of Global Optimization 30(2004) 301–318.

[8] J. Jhen-Yan, L. Kun-Chou, Array pattern optimization using electromagnetism-like algorithm, AEU – International Journal of Electronics and Communications 63 (2009) 491–496.

[9] E. Lutton, P. Martinez, A genetic algorithm for the detection 2-D geometric primitives on images, in: Proceedings of the 12th International Conference on Pattern Recognition, 1994, pp. 526–528.

[10] Z. Naji-Azimi, P. Toth, L. Galli, An electromagnetism metaheuristic for the unicost set covering problem, European Journal of Operational Research 205 (2010) 290–300.

[11] A. Rocha, E. Fernandes, Modified movement force vector in an electromagnetism-like mechanism for global optimization, Optimization Methods & Software 24 (2009) 253–270.

[12] P.L. Rosin, H.O. Nyongesa, Combining evolutionary, connectionist, and fuzzy classification algorithms for shape analysis, in: S. Cagnoni et al. (Eds.), Proceedings of the EvoIASP, Real-World Applications of Evolutionary Computing, 2000, pp. 87–96.

[13] Pal, S.K.; Bandyophadyay, S. & Murthy, C.A. (1998), Genetic algorithm for generation ofclass boundaries. IEEE Trans. On Systems, Man and Cybernetics B, 28(6), pp. 816-828.

[14] J.R. Van-Aken, An efficient ellipse drawing algorithm, CG& A 4 (1984) 24–35.

[15] L. Xu, E. Oja, P. Kultanen, A new curve detection method: randomized Hough transform (RHT), Pattern Recognition Letters 11 (1990) 331–338.

[16] J. Yao, N. Kharma, P. Grogono, Fast robust GA-based ellipse detection, in: Proceedigns of the 17th International Conference on Pattern Recognition ICPR-04, Cambridge, UK, 2004, pp. 859–862.