Chapter 3

Automatic Detection of Optic disk from Fundus Images of ROP Infant Using 2D Circular Hough Transform

In this chapter, a method of automatic detection of an Optic Disk in low-contrast infant's digital fundus images based on circular Hough transform is proposed. Number of dimensions of normal circular Hough Transforms histogram is reduced from 3 to 2 dimensions based on an approximation of OD radius. First few circles are approximated by using maximum points from Hough space. A circle with the best fit to OD edge image is chosen. The results are validated with ophthalmologists' hand-drawn ground truth. The overview of Circular Hough Transform, methodology, experimental verification, experimental results, conclusion and discussion are included in this chapter.

3.1 Overview of Circular Hough Transform

The Hough transform is a technique to identify the locations and orientations of certain types of features in a digital image. The transform consists of parameterized description of a feature at any given location in the original image space. A multi-dimensional array in the space defined by these parameters is then generated. At each point, a value is accumulated, indicating probability of an object generated by the parameters defined at that point fits the given image. Any points in the array that have relatively higher values are used to describe features that may be projected back onto the image. The higher to value, the bigger possibility that the features actually present in the image (Gonzalez, 2002).

In essence the Hough Transform produces a set of parameters which describe a boundary curve of the expected type that represents the best fit to the set of edge points in the given image. This is done by transforming every edge position in the image 'space' (as defined by x and y axes) into a corresponding curve within a 'parameter space', or 'Hough space'. A point in the Hough space where many curves intersect represents a simultaneous solution to the parametric equation for all of the edges in the image space whose coordinates gave rise to those curves. This indicates a strong likelihood of a boundary shape of the expected type having been detected in the image space. The coordinates of the point of the intersection in the Hough space correspond to the parameters of the curve detected in the image space; the greater the number of intersections, the greater the confidence that the detected boundary shape is genuine. It is this 'voting' effect that gives the Hough Transform its characteristic immunity to noise and discontinuous boundaries.

For example, consider the case where a straight line is to be detected. A point, (x_i, y_i), in input space presumed to lie on this line (conventionally defined by the standard linear equation, $y = mx + c$) produces a locus of points in parameters space for all possible lines upon which it could lie (thus defined as $c = -mx + y$), as shown in Figure 3.1. A second point in input space, (x_j, y_j), similarly produces a locus of points in Hough space. Thus when all points of interest in input space (previously detected edges) have been transformed to loci in Hough space, the intersections of these loci give a vote as to the best set of parameters for the unique line in the input space which will join all given points. The position of maximum intersection yields the parameters m_b for the best fit solution.

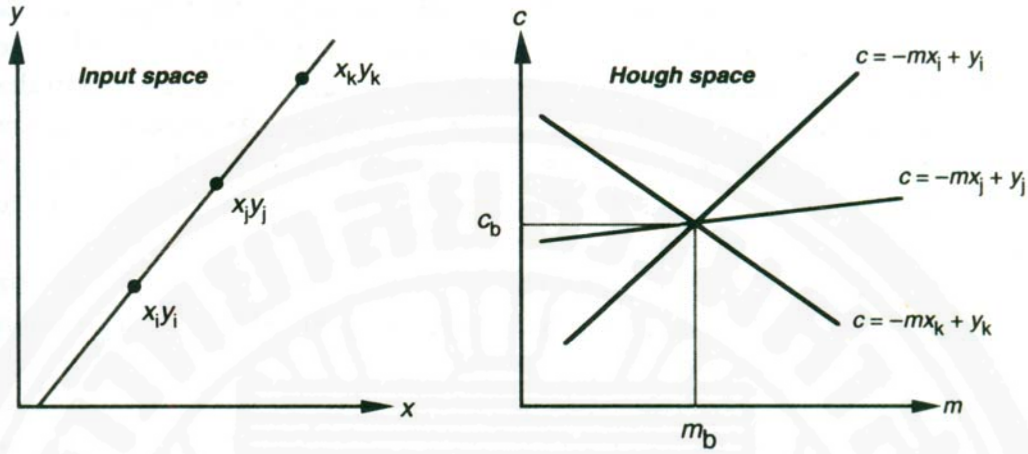


Figure 3.1. The Hough Transform used for straight line detection

One problem with this approach is that when implemented in discrete digital form a very large array of Hough space 'accumulators' is required to store all possible votes since the range of values should extend from minus infinity to infinity (e.g. a perfectly vertical line in input space has an infinite gradient). One way to overcome this limitation is to utilize polar coordinates length, r, and angle, ø, of normal vector connecting it to the origin (see Figure 3.2). These parameters are related to the x and y coordinates by the expression

$$r = x\cos\phi + y\sin\phi \qquad (3.1)$$

The three points shown in the input image are mapped into the Hough space (now in (r,ϕ) form). Each point in the input image, a, b or c, transforms to a sinusoidal curve which is plotted over the range 0 to 2π radians. The position of maximum intersection can again be found and these unique values of r_b and ϕ_b used to define the best straight line detected in the input image which joins the given pixel points, of edges. As expected all the curves exhibit a symmetrical positive and negative response. Therefore the amount of computation can be halved by plotting curves in the Hough space only over the range 0 to π radians (Awcock and Thomas, 1996).

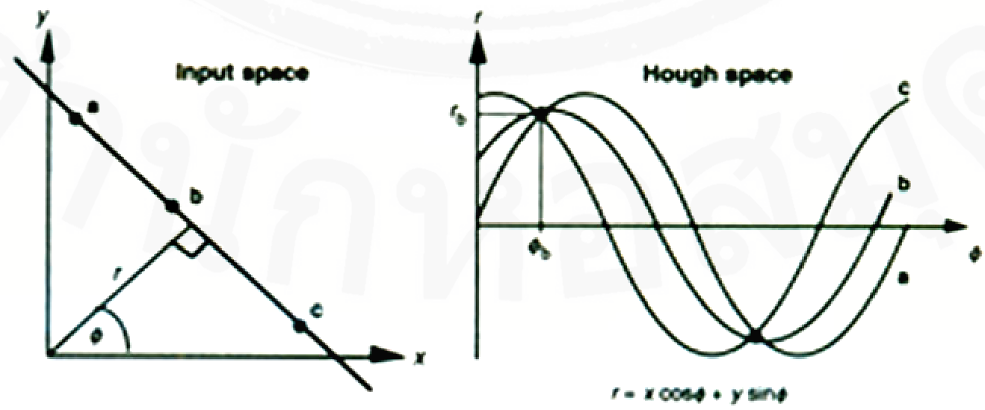
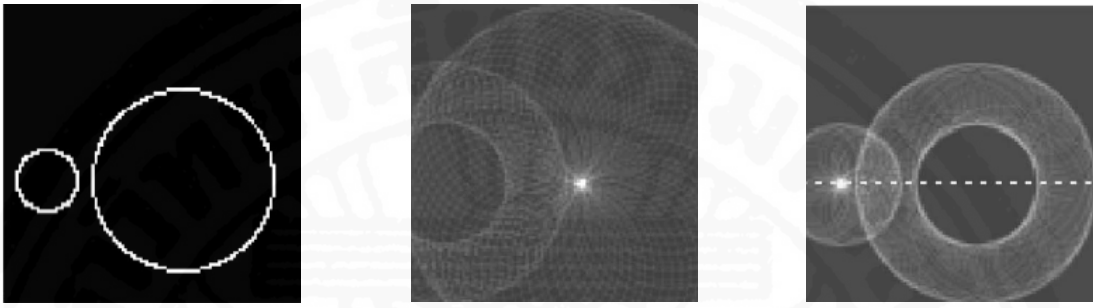


Figure 3.2. The Hough Transform-polar representation

In Figure 3.3, the Hough transform can be used for representing objects that can be parameterized mathematically. For example, in our case, a circle can be parameterized by an Equation. (3.2).

$$(x-a)^2+(y-b)^2=r^2 \qquad (3.2)$$

where *(a,b)* is the coordinate of the center of the circle that passes through *(x,y)* and *r* is its radius. From this equation, it can be seen that three parameters are used to formalize a circle which means that Hough space will be a three-dimensional space for this case.



(a) (b) (c)

Figure 3.3 a) Binary dataset consisting two circles of radii 10 and 30 units b) result of using circular Hough Transform to find circles of radius 30 units c) result of using circular Hough transform to find circles of radius 10 units

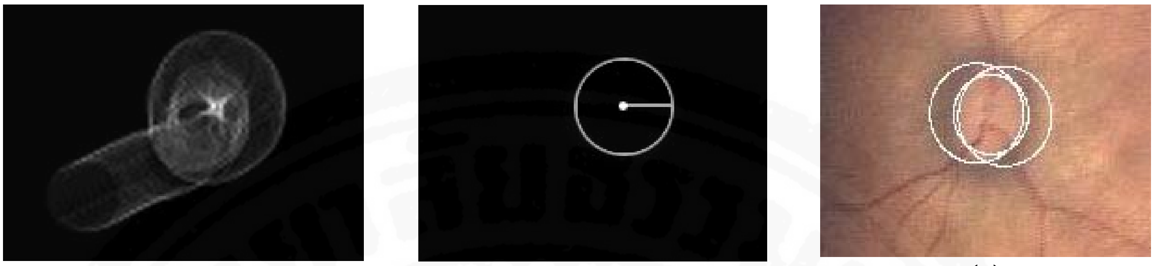
3.2 Methodology

3.2.1 Edge Detection

Some specific properties of the infant's fundus images are that they are low contrast and very noisy. However, only the edge of the OD's circular shape is needed to calculate the Hough Transform. In order to get rid of noisy and unwanted information, Canny Edge operator was experimentally chosen and applied to the image as the first step in this process. This technique removes most of the noise due to the fine texture leaving only the required edges of the OD. Experimentally, we found that the Canny Operator with the following parameters gives the best result: $\sigma = 1$ and the window size is 5 x 5.

3.2.2 First approximation of Optic Disk

Normal circular Hough transform requires very high computational power because it is needed to form a 3D histogram. We tried to reduce dimensions of the histogram to two dimensions, based on an approximation of the first known OD radius. From our test set of images, statistically, we found that size of most of the OD radii are between 20 pixels and 25 pixels. This prior information can be used to reduce dimensionality of the Circular Hough histogram from 3D to 2D for better accuracy and faster calculation. During the calculation process, the accumulator parameter array are filled according to each of the above radii, where each array composed of cells for the *(x,y)* coordinates of the center of the potential circle. The edge image is scanned and all the points in this space are mapped to Hough space using an Equation (3.2). A value in particular point in Hough space is accumulated if there is a corresponding point in the image space. The process is repeated until all the points in the image space are processed. The resulting Hough transform image was scaled so all the values lie between 0 and 1. Then it was thresholded to leave only those points with high probability of being the centers. Then the different regions were matched by different circles. The output image is computed by drawing circle with these points and adding this to the input image as shown in Figure 3.4. In order to reduce the chance that there is more than one thresholded points staying closed together. The resulting 2D histogram will be sent to dilation and erosion functions, so these points will be combined as one final point.



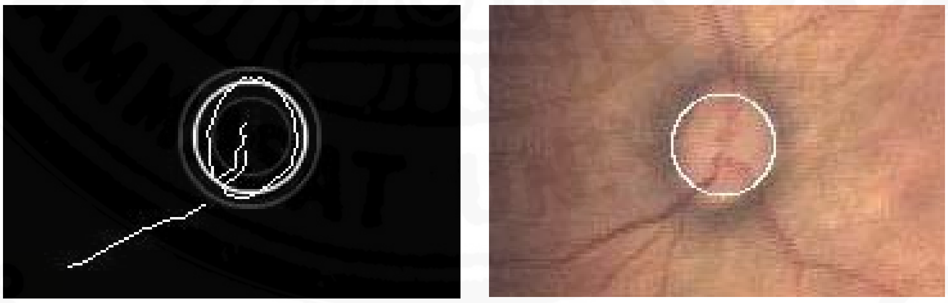
(a) (b) (c)

Figure 3.4 (a) A part of an resulting image after applying 2D circular Hough transform (b) Result of matching the circle to the high probability point with 20-pixel radius (c) First few approximation of circle

3.2.3 Finding Best Circle

A set of approximated circles from the previous step will be compared in this step. The best circles of this set would be the circle that fits most of the OD edges. In this step we counted the number of pixel which is in the vicinity of the detected circle's edge. A mask in a shape of a donut is put on the binary edge image on the same location of each of the detected circle. From the statistical experiment, the best width of the donut ring is five pixels. Number of edge pixels under this mask will be counted and compared for all the detected circles.

The pixel counting is normalized by this formula, $X = detected\ pixels / 2\pi r$, a number of detected pixels divided by the total curriculum of an approximated circle as shown in Figure 3.5. The value shows the percentage of edge pixel being detected. The highest percentage means that the circle is best to use to locate the optic disk.



(a) (b)

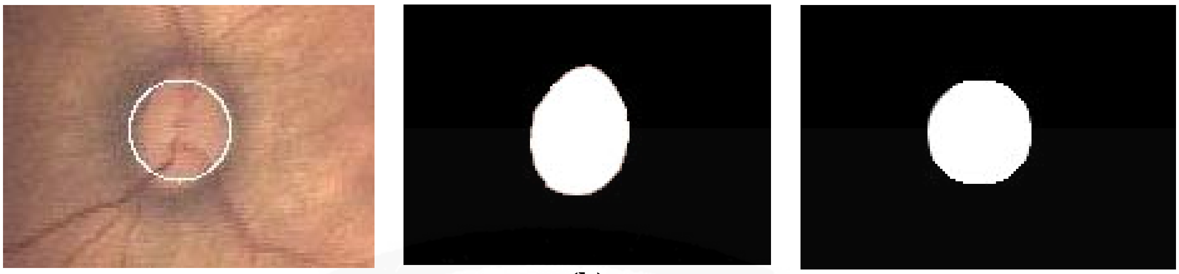
Figure 3.5 (a) Using a mask shape of donut (b) The best detected circle

3.3 Experimental Verification

The results were clinically validated in this step. All images in our test set are sent to ophthalmologist to identify the OD manually. All the OD's which are automatically detected by our system are then compared with clinician's hand-drawn ground truth. Figure 3.6 shows an example of both ground truth image and our detection result. The hand-drawn and detected optic disk images are represented in white. Number of pixels of the detected image that intersected with pixels of the hand-drawn image will be summed and compared with the number of pixels on the hand-drawn ground truth as demonstrated in Table 3.1.

Table 3.1 The examples of comparison result of intersected pixels on selected images.

Image ID	Image Name	Detected pixels	Ground truth pixels	Accuracy (%)
1	A1	1152	1175	98.5
2	A2	1215	1332	95.1
3	A11	1236	1312	94.2
4	A12	1295	1401	92.4
5	A13	1261	1416	89.1
6	A14	1125	1470	76.5
7	A15	1257	1510	83.2
8	A16	1205	1549	77.8
9	A17	1243	1567	79.3
10	A19	1363	1661	82.1
11	A20	1315	1809	72.7
12	A3	1047	1177	89.0
13	A5	1325	1530	86.6
14	A7	1291	1470	87.8
15	A8	1248	1538	81.1
16	B2	1301	2015	64.6
17	B3	1109	1281	86.6
18	B5	1227	1517	80.9
19	B7	1259	1542	81.6
20	B8	1240	1497	82.8
21	B9	1267	1663	76.5
22	B10	1315	1531	85.9
23	B11	1224	1558	78.6
24	C2	1404	1565	89.7
25	C5	1362	1374	99.6
26	C7	1286	1582	81.3
27	D14	1262	2107	59.9
28	E1	1291	1914	67.5
29	E3	1184	1836	64.7
30	D6	1129	1644	68.7
31	C8	1273	1598	79.7
32	C10	1207	1536	78.9
33	C11	1124	1319	85.2
34	C12	1150	1331	86.4
35	C13	1199	1380	86.9
36	C14	980	1137	86.2
37	C20	1634	2094	78.0
38	D2	1143	1360	84.0
39	D4	1188	1495	79.5
40	D7	1158	1370	85.0
41	D8	1225	1531	80.0
42	D10	1545	1792	86.6
43	D12	2610	3410	76.5
44	D13	2521	2530	99.6
45	E7	1158	1354	85.5
46	G1	1276	1712	74.5
47	G2	1305	1954	66.8
48	G3	1235	1532	80.6
49	E13	1363	1669	82.0
50	G4	1253	1791	70.0
Overall				**81.7**



(a) (b) (c)

Figure 3.6 (a) OD automatically detected by our system (b) Clinician's hand-drawn ground truth (c) Detected pixels

All of the processes are concluded with a flow chart in a Figure 3.7.

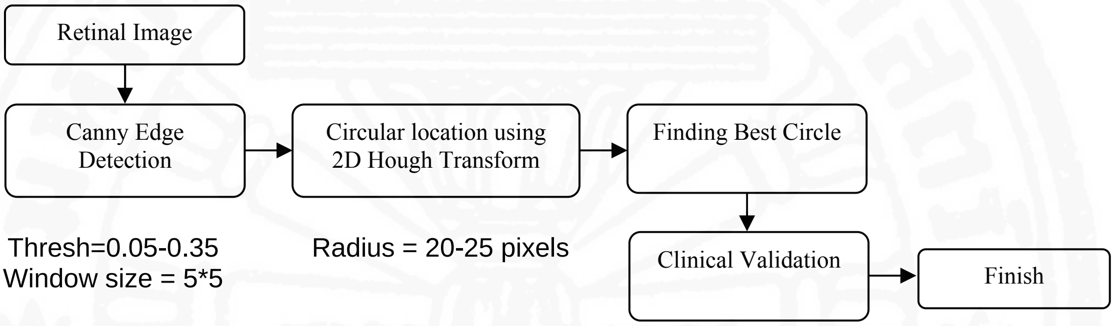


Figure 3.7 Showing a flowchart of 2D Circular Hough Transform process

3.4 Experimental Results

The method is tested using a randomly selected set of fifty images. The accuracy result is demonstrated by a graph in Figure 3.8. The chart represents the OD performance evaluation for each image. We found that the average of the accuracy by this method is 81.7 % and the total processing time is 12 seconds for each image with 3 GHz Pentium 4 machine.

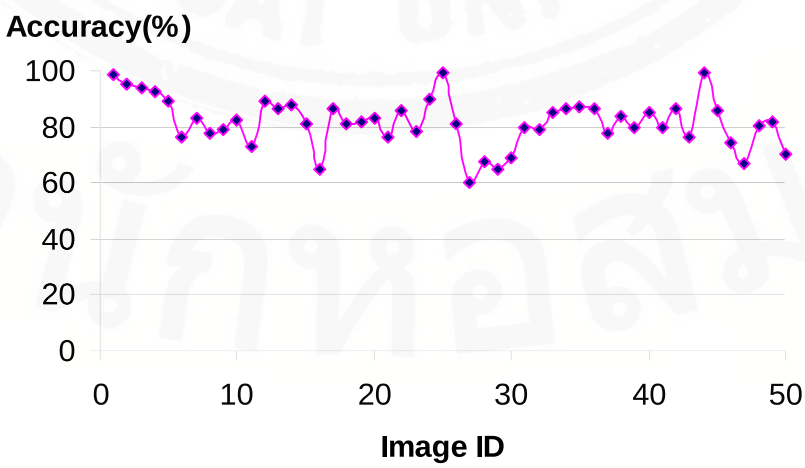


Figure 3.8. Showing the accuracy result of 2D Circular Hough Transform technique

3.5 Conclusion and Discussion

This method is based on canny edge detection and circular Hough transform technique. A prototype has been implemented in MATLAB 7.0.4(R14) on a 3GHz PC under Windows XP. It was tested using a data set of fifty infant's fundus images. From this experiment, the rate of optic disk detection for each image is 12 seconds. The OD position was considered correctly detected if the pixels in the detected image present in the clinician's hand-drawn ground truth. This method was able to locate the position of OD with a high 81.7% accuracy. This technique works pretty well even though the input image is in a low-contrast condition.