34th Annual International Conference of the IEEE EMBS
San Diego, California USA, 28 August - 1 September, 2012

Centroid extraction from Hartmann-Shack images using swarm clustering approach

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Abstract—**Image analysis of Hartmann-Shack Wavefront sensor is practically useful to extract complex refractive aberrations in the retina. However due to noises such as lens glares, reflections, occlusions or extreme aberrations, pinpointing centroid locations of these lenslets prove to be a challenging problem. In this paper we propose a novel automatic extraction of lenslet foci using Rapid Centroid Estimation (RCE) and Artificial Centroid Injection (ACI). Using this method we are able to extract as much as 86% of total lenslets' centroids before injection and 97% of total lenslets' centroids after injection on average based on experimental data on 20 Hartmann-Shack images of off-axis aberration in the human eye. Our technique advantage is that it does not require any prior fine tuning.**

I. INTRODUCTION

The Hartmann-Shack (HS) sensor is a wavefront sensor that is often used by optometrists to analyze higher order aberrations of the human eye. The HS sensor consists of a Charge-Coupled Device (CCD) camera which is used to capture the focus of a lens array called lenslets. By computing the displacements of these lenslets from their specified focal points, wavefront error can be measured. Eye aberration can then be analyzed by reconstructing the wavefront by computing the coefficients of Zernike polynomials [1].

Software based solutions to unwrap these images requires quality extraction of foci coordinates [1-2]. There is therefore a preference for algorithms that are able to precisely pinpoint centroid locations and recover missing or occluded centroids. Recently advanced image processing methods have been proposed in order to reliably extract the centroid coordinates of HS lenslets [1-4]. Yin proposed a dynamic thresholding method using a dynamic windowing method. The algorithm is tested with image data generated using a Spatial Light Modulator (SLM) [3]. In our recent study on HS images of off-axis aberration, we proposed a software based technique for unwrapping images with missing points and occlusions using Kalman Filter and General Regression Neural Network [4]. Yin's algorithm was used to determine centroid seed for the algorithm [4].

In this paper we propose a novel centroid extraction method based on image clustering using swarm intelligence. We will demonstrate the capability of Swarm Rapid Centroid Estimation+ (Swarm RCE+) algorithm to extract centroid locations from noisy HS images. Artificial Centroid Injection (ACI) algorithm will be used to estimate missing and occluded centroids [4].

Section II presents the overview of the algorithm. Section III explains the proposed method. Section IV presents the experimental results and discussions. Finally section V provides conclusions.

II. OVERVIEW

The algorithm can be divided into four stages: image pre-processing, image clustering, Region of Interest (ROI) determination, and centroid injection. In the image pre-processing, we emphasize contrasting higher intensity spots using a Laplacian of Gaussian (LoG) filter. The resulting image is clustered using Swarm Rapid Centroid Estimation (Swarm RCE+). This process produces a logical map of the centroid locations. Dilating and eroding this logical map we then determine the ROI of the HS image. Given good centroid locations and ROI have been found, recovery of missing centroids using ACI can be carried out.

III. METHOD

A. *Image pre-processing*

The image pre-processing in our centroid extraction algorithm is relatively simple, however it is an important part of the algorithm. We have discovered that given the source image provides clean information, higher intensity spot can be determined using an 8 by 8 Laplacian of Gaussian (LoG) kernel with standard deviation of 0.5 [4].

B. *Image Clustering using Swarm RCE+*

Characteristic spots can be extracted from the LoG filtered image by manually setting the global threshold. However, using such hard global thresholding method, some of the lower intensity peaks fall below intensity threshold and do not get extracted as a result. Another preferable approach is to perform windowed thresholding using Yin's algorithm. This algorithm employs an automatically adapting the threshold for each window based on the histogram of each window and taking a specific bin as the threshold. We have previously used this algorithm and it works well on our experimental images after fine tuning the parameters including window size and the size of histogram bin [4].

In general case, we propose that we require an algorithm that is capable of operating on the global image and does not need fine tuning. Considering that, we propose to use

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clustering method to separate between background and the variable intensity spots. In our application we propose to use Swarm RCE+ as the clustering algorithm [5-7]. RCE is proposed as a variant of PSC algorithm with reduced time complexity. This algorithm is capable of achieving the performance of PSC with higher stability and faster optimization speed [5-6]. Strategies for RCE including substitution strategy and swarm strategy have been recently proposed [7].

Swarm RCE+ is used to separate the image to two clusters: spots and background based on pixel intensity. The image dimension is 494 by 656 pixels. The clustering process is done collectively by 4 RCE+ groups. Each RCE+ group consists of 2 particles, each representing a centroid candidate. These two particles search for equilibrium by gravitating towards nearest cluster's centre of mass [5-7].

The meter used to measure the fitness is within class and between class ratio (S_w/S_b) as is defined in (1-3) [7].

$$S_w = \frac{1}{N}\sum_{\forall i}\sum_{\forall j \in x_i}(y_j - x_i)(y_j - x_i)^T \tag{1}$$

$$S_b = \frac{1}{N}\sum_{\forall i} N_{j \in x_i}(x_i - \mu)(x_i - \mu)^T \tag{2}$$

$$f(t) = \frac{S_w}{S_b} \tag{3}$$

Where N denotes the total number of data points in the set, y_j denotes intensity of input pixel j, x_i denotes coordinate of cluster centroid/particle i. $N_{j \in x_i}$ denotes the number of data points that belong to cluster/particle x_i. μ denotes data mean.

Figure 1 and Figure 2 illustrates particle position and fitness development for Swarm RCE+. In these figures 4 groups of RCE+ searches for best position combination. The best fitness is found at iteration 28 with positions of 27.26 and 0.3081. These positions correspond to spots and background.

Figure 3 shows fitness development of Swarm RCE+ compared to K-means. This graph shows the advantage of Swarm RCE+ to K-means in escaping local minima positions.

Figure 4 shows the results of this method on clustering four noisy HS images.

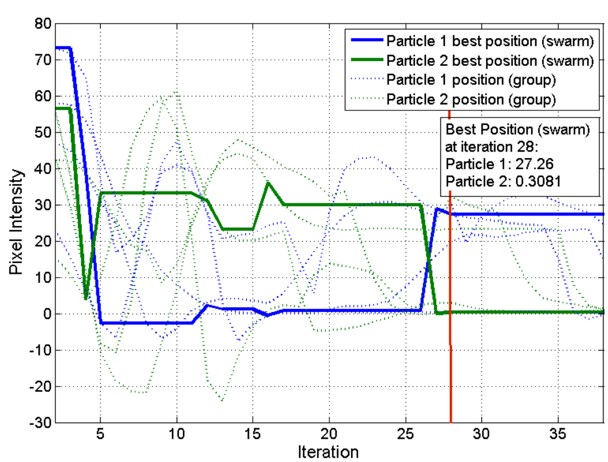

Figure 1. Swarm RCE+ Particle position development.

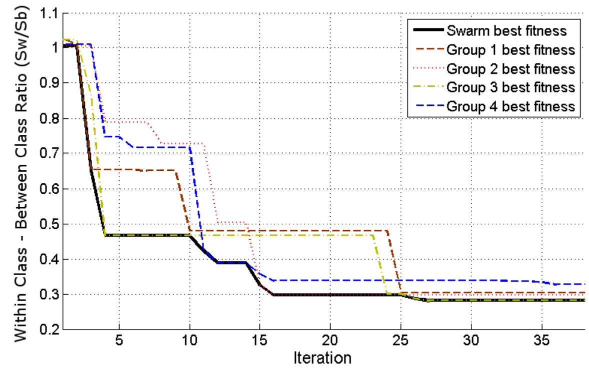

Figure 2. Swarm RCE+ fitness development.

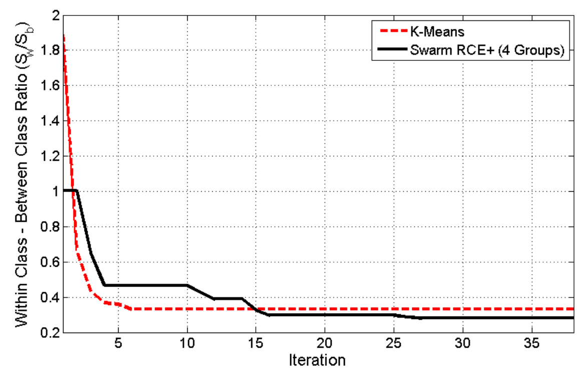

Figure 3. Swarm RCE+ compared to K-means fitness development.

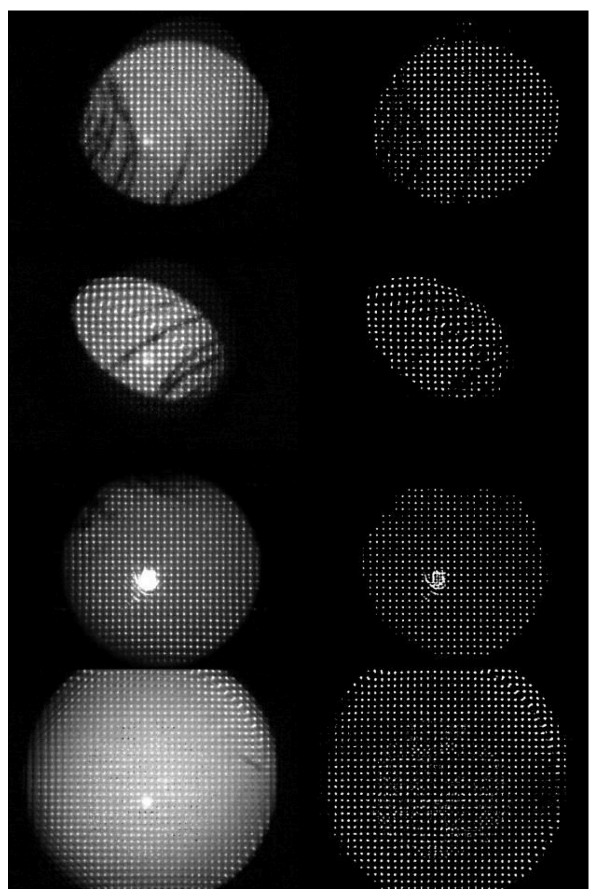

Figure 4. Swarm RCE+ clustering results on four noisy HS images

C. *Determining Region of Interest using morphology filter*

After obtaining the logical map, the ROI can be determined by applying dilation and erosion to the logical map. A dilation using disc operator with radius of 20 pixels is carried. The process is followed by erosion using disc operator with radius of 12 pixels. This process will combine all focal spots into one monolithic blob specifying the ROI. The Elliptical ROI characteristics including ellipse centre, orientation, and length of major and minor axis can be easily extracted from the characteristic of the blob. The result of the ROI for HS images in Figure 4 can be seen in Figure 5.

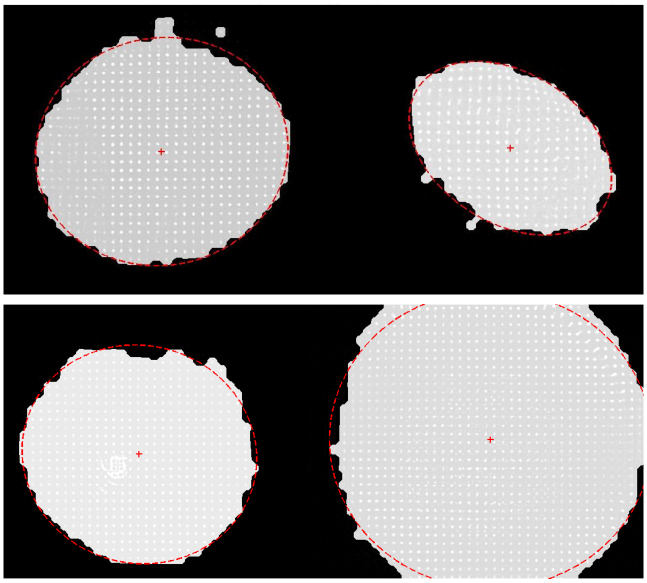

Figure 5. ROI determined using dilation and erosion

D. *Centroid Extraction and Artificial Centroid Injection*

The centroid extraction is done by simply calculating the center of mass of each blob in the logical map. Blobs which volume are less than 15 pixels and eccentricity of more than 0.95 are considered noise and discarded. Centroids will be extracted from the remaining blobs. Centroids that are very close together in Euclidean space are also discarded.

We perform ACI to the found centroids to recover missing or previously undetected centroids [4]. The steps of the method can be briefly described as follows. Firstly, centroids are grouped vertically and horizontally using vertical and horizontal Kalman Filter. These groups are used to train General Regression Neural Networks (GRNN). From these networks we estimate the linear trend of each group and create a set of centroid estimates from the intersection points of the lines. The result of centroid extraction and injected centroids after ACI algorithm can be seen in Figure 6. Extracted centroids are labeled as green circles, ACI injected centroids are labeled as blue triangles.

IV. RESULTS AND DISCUSSIONS

The algorithm was tested using 29 off-axis HS images from five participants. The extraction results from 20 images are presented in this study. All the images have occlusions and lens glares of variable degree. The images measures off axis angles from 50º Nasal to 50º Temporal from each subject. From these images we compare the result of global thresholding method, Yin's dynamic windowed thresholding which is fine-tuned to our application, K-means clustering, and our proposed swarm RCE+ clustering method. The swarm contains 4 RCE+ groups. Probability of a particle to enter substitution is set to 2% per iteration. Maximum stagnation is set to 10 iterations. The results are presented in Table I.

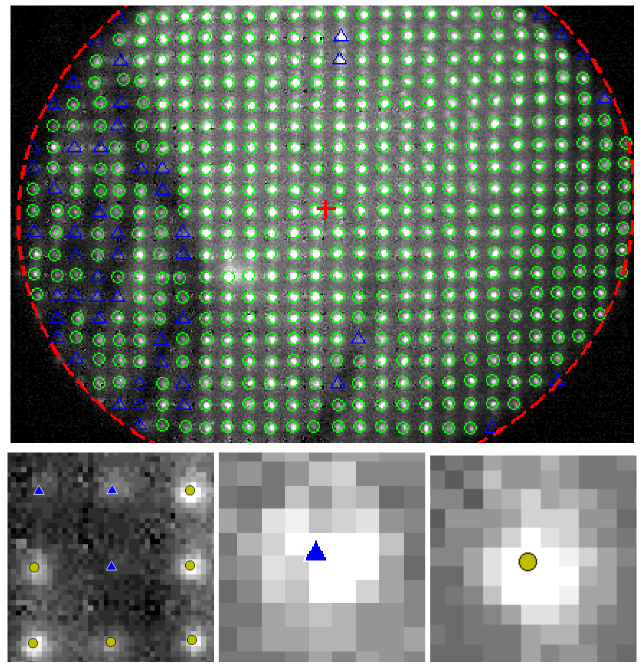

Figure 6. Extracted Centroids (green circles) and Injected Artificial Centroids (blue triangles) on different magnification scales

TABLE I. CENTROID EXTRACTION RESULTS

No	Description[b]	% of extracted centroids before/after ACI[a]							
		Global Threshold		*Dynamic Threshold*		*K-means*		*Swarm RCE+*	
1	1/0º/Ast	78%	91%	79%	91%	90%	97%	93%	99%
2	1/50ºN/SA	86%	99%	86%	99%	83%	96%	85%	99%
3	1/30ºT/SA	79%	90%	83%	92%	79%	91%	79%	91%
4	2/50ºN/Ast	77%	93%	82%	95%	77%	97%	78%	98%
5	2/0º/Ast	81%	91%	85%	92%	78%	92%	81%	91%
6	2/50ºT/Ast,defc	84%	96%	85%	92%	81%	96%	82%	98%
7	3/0º/Piston	83%	94%	87%	92%	88%	96%	89%	97%
8	3/10ºN/Piston	88%	99%	90%	99%	89%	99%	92%	99%
9	3/20ºN/Piston	88%	93%	94%	98%	88%	93%	90%	99%
10	3/30ºN/Piston	88%	100%	92%	100%	92%	100%	92%	100%
11	3/40ºN/Piston	96%	100%	100%	100%	98%	100%	98%	100%
12	3/30ºT/Piston	95%	97%	88%	98%	93%	97%	93%	97%
13	3/50ºT/Piston	87%	93%	94%	100%	91%	100%	91%	100%
14	4/50ºN/Ast,defc	89%	99%	91%	99%	92%	99%	93%	99%
15	4/40ºN/Ast,defc	90%	98%	93%	100%	88%	98%	90%	98%
16	4/0º/Ast	81%	95%	86%	95%	90%	96%	90%	96%
17	4/10ºT/Ast,defc	76%	94%	93%	99%	96%	99%	94%	99%
18	4/20ºT/Ast,defc	51%	86%	51%	86%	51%	86%	81%	91%
19	5/20ºT/Ast	63%	95%	53%	97%	65%	97%	65%	97%
20	5/30ºT/Ast	43%	80%	48%	84%	66%	94%	69%	93%
Mean		80%	94%	83%	95%	84%	96%	86%	97%
S.Dev		14%	5%	15%	5%	12%	4%	9%	3%

a. left column indicates %centroids extracted from the logical map, right column indicates %centroids extracted after ACI algorithm

b. description is written as follows: subject number/degree of off-axis/type of aberrations including Piston, Spherical Aberration (SA), Astigmatism (Ast), Defocus (defc)

We carry another experiment using both K-means and Swarm RCE+ to cluster a randomly selected image from each subject. The experiment is repeated 20 times for each image.

Table II presents the clustering results of K-means and swarm RCE+ on the HS images on Table I. The performance metric used in this study is the within cluster and between cluster ratio (S_w/S_b) and total intra-cluster Euclidean distance.

TABLE II. CLUSTERING RESULTS

Image No[a]	Performance Metric	Algorithm[b]	
		K-means	***Swarm RCE+***
1	S_w/S_b	0.352 ± 0	0.296 ± 0.0068
	Euclidean Dist	949 ± 0	780 ± 198
	Time (s)	0.32 ± 0.02	7 ± 3
4	S_w/S_b	0.431 ± 0	0.36 ± 0.0259
	Euclidean Dist	847 ± 0	614 ± 206
	Time (s)	0.33 ± 0.061	5.1172 ± 3.56
11	S_w/S_b	0.365 ± 0	0.316 ± 0.014
	Euclidean Dist	891 ± 0	661 ± 218
	Time (s)	0.39 ± 0.063	6.75 ± 3.44
14	S_w/S_b	0.35 ± 0	0.298 ± 0.01
	Euclidean Dist	994 ± 5	853 ± 257
	Time (s)	0.324 ± 0.1	6.35 ± 3.17
20	S_w/S_b	0.325 ± 0	0.29 ± 0.02
	Euclidean Dist	840 ± 6	1047 ± 51
	Time (s)	0.27 ± 0.03	6.29 ± 3.34

a. Image number corresponds to images in Table I

b. Shaded cell indicates better result

Table I shows that centroid extraction method based on clustering methods such as K-means and Swarm RCE+ produce relatively more stable result compared to thresholding methods. On less noisy situations dynamic thresholding methods works relatively better than clusterin

g methods. For noisy situations such as image 16 to 20 clustering methods produces better results. Particularly for image 18, where there is a glare and reflection noises on the image. Global thresholding achieves the least optimum results as compared to the other three methods. Table I also shows that the ACI algorithm generally improves the extraction results. The centroids extracted from HS image number 18 using different algorithms can be seen in Figure 7. It can be seen that on this image RCE extracts more centroids than other methods. In all techniques the ACI algorithm successfully injected centroids (blue triangles) to the appropriate undetected focal spots.

Table II shows that Swarm RCE produces consistently lower S_w/S_b compared to K-means. On every trial on each image K-means centroids converge on same coordinates which are most likely local minima coordinates. This is clearly shown in the very small standard deviations on S_w/S_b and Euclidean Distance on all five images. Despite the more optimal results, improvements are possible as Swarm RCE+ still has much longer optimization time compared to K-means.

V. CONCLUSIONS AND FUTURE DIRECTION

The results of this pilot study suggest that clustering techniques such as K-means and Swarm RCE+ are robust alternatives to extract lenslet centroids from noisy HS images. Clustering based approaches also have advantage that they do not require parameters fine tuning. We have shown that on this particular experimental data Swarm RCE+ produces relatively better results compared to K-means, dynamic thresholding, and global thresholding approaches. We have also shown that ACI algorithm increases the extraction rate of good centroids given good prior extraction.

We have demonstrated Swarm RCE+ capability on searching more optimal centroid locations to conventional K-means on our experimental data. In the future we intend to further reduce Swarm RCE+ algorithmic complexity. We will also implement Swarm RCE+ on other clustering cases.

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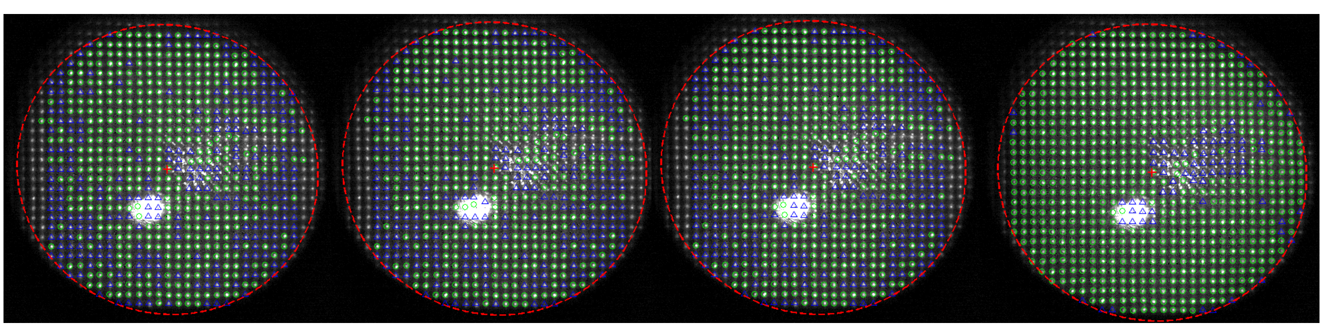

(a) (b) (c) (d)

Figure 7. Centroids extracted from HS image 18 using global thresholding (a), dynamic windowed thresholding (b), K-means (c), and Swarm RCE+ (d)