Revista EIA, ISSN 1794-1237 / Year XI / Volume 11 / Issue N. 21 / January-June 2014 / pp. 53-63
Technical-scientific biannual publication / Escuela de Ingeniería de Antioquia —EIA—, Envigado (Colombia)

OPTIC DISC DETECTION IN RETINAL IMAGES USING AN EVOLUTION STRATEGY (μ+λ)

Germán Sánchez Torres[1]
Albeiro Espinosa Bedoya[2]
Yony Fernando Ceballos[3]

ABSTRACT

In this paper we present an optic disc (OD) detection approach based on evolution strategy (ES). The approach has two main steps: coarse detection and contour edge refinement. Coarse detection estimates an approximate position using an ES in which each individual has a fitness function based on the amount of bright pixels and the number of vasculature structure edge pixels inside a circle. The contour edge refinement uses a geometric approach to circle deformation in order to adjust the circle's edge to the OD edges. To do so, the pixel with the greatest intensity value variation along a normal line is considered. The proposed approach was evaluated using the STARED and DIAREDB public repositories to process images of normal patients and those with retinal variations. The results show that the proposed method identifies the optic disc position in retinal images with an accuracy of nearly 96%.

KEYWORDS: Evolution strategies; Optic disc; Retinal images; Retinopathy.

DETECCIÓN DEL DISCO ÓPTICO EN RETINOGRAFÍAS MEDIANTE UNA ESTRATEGIA EVOLUTIVA (μ+λ)

RESUMEN

En este artículo se presenta un procedimiento para la detección del disco óptico (DO) en retinografías, mediante un algoritmo evolutivo. El procedimiento tiene dos etapas principales: la detección gruesa de la posición del DO y el refinamiento de los bordes del contorno. La detección gruesa ubica la posición del DO mediante un algoritmo evolutivo, cuyos individuos tienen como función objetivo la cantidad de píxeles brillantes y el número de bordes de la red de conductos sanguíneos, contenidos dentro de una circunferencia. La etapa de refinamiento aplica un procedimiento geométrico, para deformar el círculo inicial, ajustando el borde de éste con la posición del píxel de mayor variación en dirección al vector normal. El procedimiento fue evaluado empleando los repositorios públicos STARE

1 Systems Engineer. Universidad del Magdalena (Colombia). PhD in Engineering - Systems and Informatics, Universidad Nacional de Colombia, Medellín (Colombia). Assistant Professor, Universidad del Magdalena, Santa Marta. R+D Group in New Information and Communication Technologies (GIDTIC).

2 Mechanical Engineer. PhD(c) in Engineering, Universidad Nacional de Colombia, Medellín (Colombia). Associate Professor, Universidad Nacional de Colombia.

3 Systems Engineer. PhD(c) in Engineering. Assistant Professor, Systems Engineering Program Instituto Tecnológico Metropolitano,

Correspondence author: Sánches-Torres, G. (Germán). Carrera 32 N. 22-08. Tel: (575) 421 7940. Ext: 1138. Email: gsanchez@unimagdalena.edu.co.

Paper history:
Paper received on: 27-V-2013 / Approved: 25-III-2014
Available online: June 30th 2014
Open discussion until June 2015

DOI: http://dx.doi.org/10.14508/reia.2014.11.21.55-66

y DIAREDB, procesando imágenes de pacientes sanos y con alteraciones de las retina, generadas por la presencia de retinopatía diabética. Los resultados experimentales muestran que el método propuesto puede identificar la posición del disco óptico en retinografías con una precisión cercana al 96 %.

PALABRAS CLAVE: estrategia evolutiva; disco óptico; retinografías; retinopatía.

ESQUEMA COMBINADO DE MOVIMENTO ÓTIMO DE TAPS E INJEÇÃO DE REATIVOS PARA REDUÇÃO DE PERDAS EM SISTEMAS DE DISTRIBUIÇÃO

RESUMO

Neste artigo apresenta-se um modelo de optimização para um esquema combinado de movimento ótimo de taps e injeção ótima de reativos em sistemas de distribuição. O modelo proposto indica as injeções de reativos e o esquema de posicionamento taps que minimiza as perdas mantendo as tensões nos limites permitidos, a custo mínimo. A formulação realiza-se através dum fluxo de potência ótimo reativo e soluciona-se usando um software comercial. Vários testes foram realizados num sistema de distribuição de 33 barras. Os resultados mostram que o uso combinado de Variação de taps e injeção de reativos conduz a uma redução maior de perdas que o uso destas ações por separado.

PALAVRAS-CHAVE: Redução de perdas; Fluxo ótimo de reativos; Sistemas de distribuição.

1. INTRODUCTION

The rapid development and mass use of optic technologies aimed at acquiring non-invasive images in medicine is opening a path for development in applied medical procedures like diagnosis, detection, and selection, which allow for the assignment of improved treatments in early stages of several illnesses.

The importance of modern optic technologies, such as MRIs, tomographies, and retinal images, among others, is based on the ease and improved quality with which scientists and physiologists can obtain information by non-invasively observing the interior of the human body (IDF, 2012). Automatic computational analysis of these images reduces the time needed to complete medical procedures, providing modern mechanisms for periodical evaluations and becoming a testing method for determining the proper moment to begin treatment (Giancardo et al. 2012).

In the specific context of medical procedures related to retinal inspection, retinography is widely used and represents one of the most commonly used medical tools for analysis of the human visual system. These retinal images facilitate the analysis of different signs related to a variety of illnesses associated with the retina. The particular interest of this paper centers on signs related to the illness called Diabetic Retinopathy.

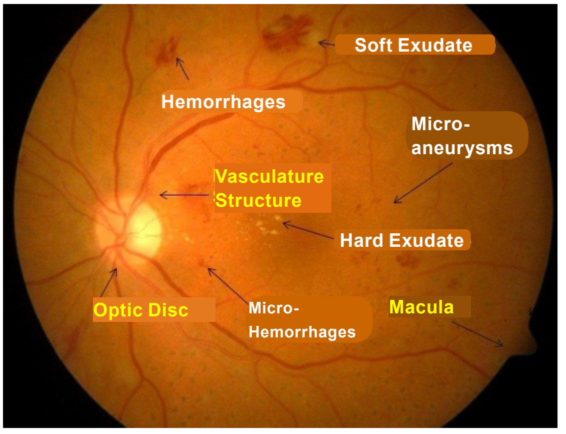
Diabetic Retinopathy is a progressive illness that is diagnosed according to certain clinical abnormalities which are difficult to detect given that the illness is asymptomatic until late stages of its development. Without proper treatment, the illness becomes a more serious pathology called diabetic macular edema (Giancardo et al. 2012, Walter et al. 2002). In addition, the International Diabetes Federation (IDF) estimates that there will be 552 million people suffering from complications related to diabetes in 2030, or 9.9% of the adult population, making it one of the most common illnesses in adults (IDF, 2012, Sujithkumar S & Vipula, 2012). This has increased the development of medical systems aimed at detecting early signs that point to the possible presence of the illness to support specialists in their diagnoses.

The computational procedures used in retinal image analysis require the identification of elements specific to ocular physiology (see **Figure 1**), including veins, blood vessels, the optic disc, and the macula. These parts must be identified in order to be calculated without ambiguity through the application of algorithms designed for the detection of specific signs related to this illness, such as hemorrhages of the presence of exudate.

In terms of the optic disc (OD), the two procedures most typically used are detection and segmentation. Detection of the OD refers to computational methods through which the position of the optic disc's center is determined using a retinal image. Segmentation of the OD refers to procedures that determine the optic disc's edge and eliminate it from the content of the image.

This article describes a procedure that handles detection and segmentation of the OD in retinal images using a search process implemented through an evolution strategy and a geometric process for segmentation of the OD's edge.

Figure 1. Different elements that can be identified in a retinal image.



2. RELATED RESEARCH

Localization methods are based on two physiological characteristics of the OD. First, the region described by the OD in an image corresponds to its brightest components (Walter et al. 2002, Giancardo et al. 2012), and secondly to the place where vascular ramifications begin. However, one important limitation related to this fact is the lack of standards regarding the technical characteristics of the image obtained through retinography. The uncontrolled variation of parameters for camera or retinography machine function can create an image in which the optic disc does not contain the brightest areas.

Another important aspect is the fact that the veins and vascular ramifications grow over the years following a parabolic trajectory which begins in the interior of the OD. These characteristics have been used in the construction of different techniques for OD localization (Sujithkumar S & Vipula, 2012). In Walter et al. (2002), a simple diagram based on thresholds is used to generate a binary map of the bright regions and select the largest group of pixels as the localization of the OD. The circular form of the optic disc was also used as a search pattern in the research done by Lu & Lim (2011) using a linear operator that analyzes image brightness along multiple segments that cross the retina. In contrast to the linear operator, but in the same general sense, in Lu (2011), a circular operator was used directly to calculate the variations of brightness in the image. Other related research includes that of Sinthanayothin et al. 1999 and Sinthanayothin et al. 2003, in which a pre-processing phase is applied to adaptively generate an improvement in the contrast on the intensity channel in the HSI (Hue, Saturation and Intensity) color space. The OD's localization was completed through an analysis of the intensity variance generated within the optic disc due to the presence of blood vessels. Another study that exploited the characteristic high presence of blood vessels in the OD was presented by Hoover & Goldbaum (2003), in which the OD is localized through a technique called diffuse convergence, which involves determining the point within the image at which the blood vessels converge. A similar idea was described by Singalavanija et al. (2006).

In general, procedures for detecting the optic disc have varied from methods based on analysis of the higher level of intensity of pixels in a grayscale representation (Lee, Wang y Lee, E. 1999), to statistical techniques like principal component analysis (PCA) (Li & Chutatape 2003; Li & Chutatape 2004) to determine the grouping tendencies of bright pixels. Other diagrams, such as models based on contours and the incorporation of area pattern recognition techniques (Lowell et al. 2004), show tendencies in the construction of new algorithms. Computational efficiency has also been considered by authors of OD localization techniques. Mahfouz and Fahmy (2010) present a rapid localization technique based on projections of image characteristics related to two-dimensional OD gradients. This allows for the reduction of the search space to just one dimension, reducing search time. Finally, diagrams based on the combination of multiple algorithms for OD detection and localization to improve results were proposed by Qureshi et al. (2012).

One important aspect to be pointed out is that not all the reported research centers on the use of retinal images that contain the presence of signs related to illness. The complexity of detecting these physiological elements in the eye increases when lesions caused by the illness are present, given that they have similar characteristics of color and shape as the eye's physiological elements. A good example of this are the exudates that form bright accumulations of the same or greater size than the optic disc in advanced stages.

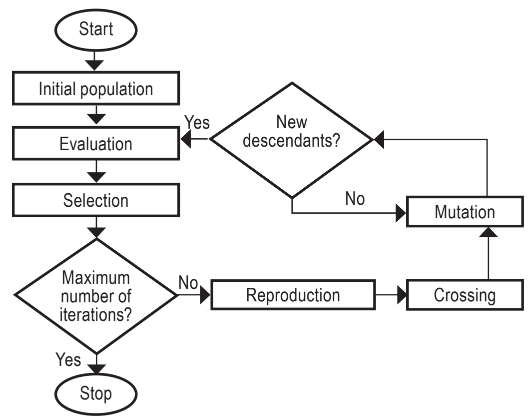
3. LOCALIZATION OF THE OPTIC DISC

Localizing the optic disc in retinal images is not a trivial process, mainly due to the multiple variations of color space because of the different ethnicities of the subjects from which the images were acquired, the imaging apparatus itself, and the optical disturbances that may give rise to clinical anomalies in the image. This is why selecting the brightest area as the location of the optic disc is not an infallible method for its detection. Therefore, an evolution strategy was designed as a search method that allows for determining the OD's coordinates in a retinal image. The search is guided by a function that mixes the two most representative physiological characteristics of the region in which the OD is located. These characteristics are: the presence of areas with a high level of whites or bright areas, and a high level of blood vessels.

Evolution strategies are heuristic techniques that imitate the evolutionary processes of species in nature and have been used for solving problems of optimization. They are based on a population of individuals and use operators of recombination, mutation, and selection in the search for the best solution in real variables.

In this study, the strategy used was ES-(μ+λ), in which a set of μ parents are used to generate λ children in each generation. In said strategy, μ parents and λ descendents make up a single set of individuals called a population. After each iteration or generation of the evolution, the best μ individuals are selected. Cross and mutation operators are applied to them to generate λ descendents. From a general perspective, evolution strategy search techniques follow the work flow sown in **Figure 2**.

Figure 2. General diagram of an evolution algorithm.



3.1. Pre-processing

The goal of this phase is to correct shadows or gradients found in the image due to the spherical form of the eye. The elimination of the gradient allows for future operations performed to be more precise, eliminating unnecessary information and reducing processing time. To achieve this, a classic median filter with a window value of 3% of the image's width is applied to a grayscale representation of the original retinal image, obtained from 70% of the green channel and 30% of the red channel in order to increase the contrast of the red zones, such as the veins, and the bright areas that make up the optic disc. The procedure applied is described in **Algorithm 1**, and the result of its application to a retinal image is shown in **Figure 3**.

Since the process takes advantage of the fact that the OD region contains a high level of blood vessels, the method requires a second image that contains the estimated edge of the vasculature structure in the retinal image. This image is estimated using an algorithm for edge detection proposed by Canny (1986) that has shown better results than other operators (Narendra & Hareesh, 2011).

Therefore, the two images obtained in the processing phase are flat, grayscale representations ($I_{normalized}$), that will be used to search for the position of the optic disc, as well as a representation of the edges of the vasculature structure's elements (I_{edges}), which will be used to estimate a component of the aptitude function of individuals (see **Figure 4**).

Algorithm 1. Image pre-processing

```
function pre_procesado( I_org, size )
   I_green = getGreenChannel ( I_org )
   I_red = getRedChannel ( I_org )
   I_pre = (0.3)I_red + (0.7)I_green;
   f_size = Width(I_pre ) * size
   I_backg ← MedianFilter(I_pre, [f_size f_size] )
   I_normalized = I_pre – I_backg
end funcion
```

Figure 3. Example of applying the image pre-processing procedure.
a) Grayscale representation, b) elimination of shadows and background ($I_{normalized}$).

a) b)

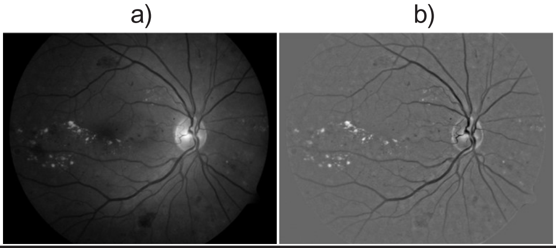
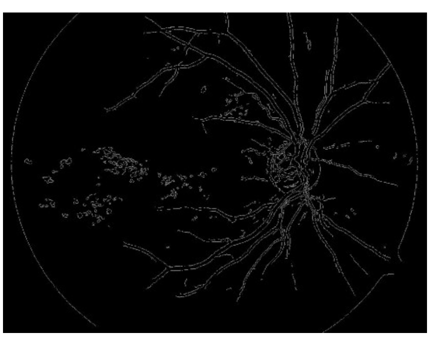


Figure 4. Pre-processing image (I_{edges}).

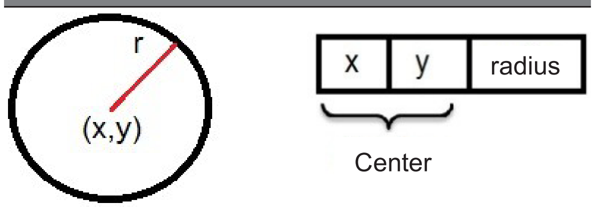


3.2. Population Representation

One of the main differences between Evolution Strategies (ES) and Genetic Algorithms (GA) is that the latter requires the definition of the functions used for coding and decoding the information contained in individuals' internal structures. This condition is not required for Evolution Strategies, given that their representation is created using vectors of real values.

Given the circular nature of the object pattern to be detected (OD), each individual represents a circle located in the coordinates (x,y) with radius r, (see **Figure 5**). The set of individuals that make up the initial population evolved by the ES is randomly generated, guaranteeing that each center is found within the retina.

Figure 5. Representation of each individual.



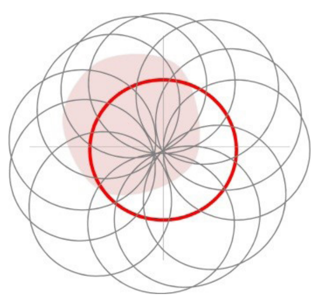
3.3. Evaluation and Selection

Each individual in the population represents a possible solution to the problem at hand. Evolution strategies require a mechanism by which to determine a measurement representative of the quality of said solution. This measurement of the individual's fitness is the function that must be maximized within the simulated evolution process. In this context, it is desirable to determine the circle with radius r that maximizes the number of bright pixels and contains the greatest number of edges of the vasculature structure. So:

$$fitness_i = f_b\,(x,y,r) + f_e\,(x,y,r) \qquad \textbf{(1)}$$

In which, $f_b\,(x,y,r)$ constitutes a percent measurement of the number of bright pixels contained within the circle represented by (x,y,r). This measurement is estimated in relation to the total of bright pixels defined as 10% of the whitest pixels in the $I_{normalized}$. image. Similarly, $f_e\,(x,y,r)$ is a percent measurement of the number of edges within the circle represented by the individual in relation to the total number of edge pixels obtained in the representation of the I_{edges}. In each iteration, λ new individuals are selected from the highest $fitness_i$ values.

Figure 6. Result of applying the local mutation operator.



3.4. Crossing and Mutation

These operators are used to generate new individuals from the initial population. A cross operator and mutation operators have been included in this model: one mutation operator that guides the global search within the retina and a local mutation operator that optimizes the adjustment of the circle's edge to the edge of the OD. The cross used corresponds to a generalized recombination model in which the value of the descendent is estimated as a factor of the sum of the parents' values, as follows:

$$C=c_1+\eta(c_1+c_2) \quad \textbf{(2)}$$

In which η corresponds to a random number with normal distribution with median zero and a standard deviation. c_1 and c_2 correspond to the values that represent the center of the circle and are applied both for coordinate *x* and for coordinate *y*. The candidates from the population to which the cross operator is applied are selected using a 10% probability.

The mutation operator is applied, altering each of the individual's values through the addition of random numbers with normal distribution, as follows:

$$C=C+N(0,\sigma) \quad \textbf{(3)}$$

In which *C* represents each characteristic in reference to the center of the circumference.

A local mutation operator is applied to the value that represents the radius. This operator aims to improve the coincidence of the circle's edge with those of the structure that represents the optic disc and is applied to the individual with the best fitness in each iteration. The radius is displaced by a random quantity around the center of the circle, generating *k* new individuals. This quantity is estimated through a normal distribution of $N(0,\sigma)$, which guarantees that small quantities of alteration are more likely.

4. SEGMENTATION OF THE OPTIC DISC

The result of the Evolution Strategy is a solution to the problem of OD localization. However, it is necessary to estimate the OD's edge so that the set of pixels that make it up can be removed to later apply specialized algorithms for analyzing or identifying bright lesions.

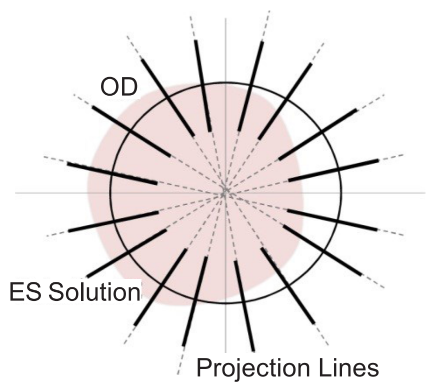
The proposed procedure for OD segmentation consists of a deformation of the given circumference as the best solution of the ES. The deformation of this circumference is performed by displacing of a set of points from the edge along a straight light estimated in the direction of the norm at that point, which is called the projection line. The direction of displacement from a point p is determined by the analysis of the intensity of the ($I_{normalized}$) image's pixels which are located along a projection line. The rate of change is calculated for this set of pixels, and the projection of point *p* will consist of the displacement of the point toward the position of the pixel that has the lowest rate of change.

The procedure begins by estimating a set *P* of *k* points uniformly distributed along the circumference. So:

$$P=\{p_1,p_2,\ldots,p_k\} \quad \textbf{(4)}$$

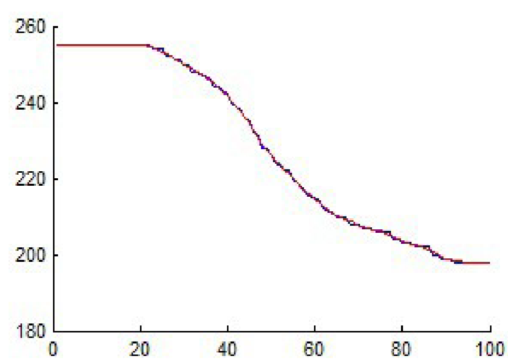
So that the arc between two pairs of consecutive points, $\widehat{p_i, p_{i+1}}$ y $\widehat{p_j, p_{j+1}}$ is equal. The value of *k* is a parameter established by the user and controls the quality of the circumference deformation. Once the set of points *P*, has been obtained, a set of straight line segments of length *l*. is estimated. Each segment is parallel to the direction of the norm for the circumference at the point of the circumference that contains it. Therefore, each segment is a portion of the line that contains the origin of the circle (x_c, y_c), and each of the points p_i. **Figure 7** illustrates the generation of projection lines for points *P*.

Figure 7. Result of the set of projection lines *k=16* on the edge of the ES solution.



It is expected that the ES solution will overlap the optic disc region in which the OD is found. Therefore, the projection lines should cross the edge at some point. This point is characterized by having the lowest rate of change if the lines from the interior to the exterior of the circumference are followed. This rate of change represents the intensity variations of the pixels along the lines. So, the intensity values of the pixels along each projection line are taken to construct an intensity curve (see **Figure 8**).

Figure 8. Graph of the average intensity along a projection line of length *l=100.*

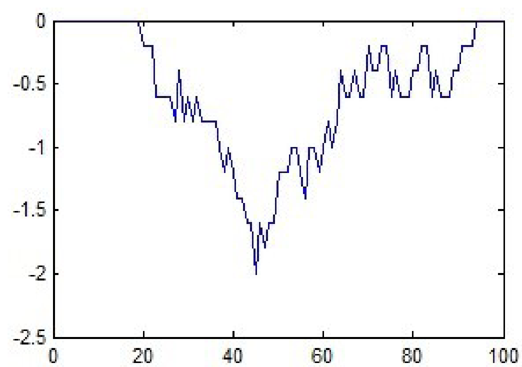


The rate of change at point pi is estimated along the intensity curve as follows:

$$tc(i) = \bar{I}(i+1) - \bar{I}(i) \quad \textbf{(5)}$$

In which $\bar{I}(s)$ represents the average intensity at point p_s, and is estimated from community of four pixels centered around p_s. If the projection line crosses the edge of the optic disc, it generates a minimum gradient value on the intensity graph (see **Figure 9**).

Figure 9. Graph of the rate of change on a projection line of length *l=100.*



Each point p_i of *P* is moved to the point with the lowest rate of change. **Figure 10** illustrates this procedure.

Figure 10. Adjustment of points p_i along the edge of the OD.

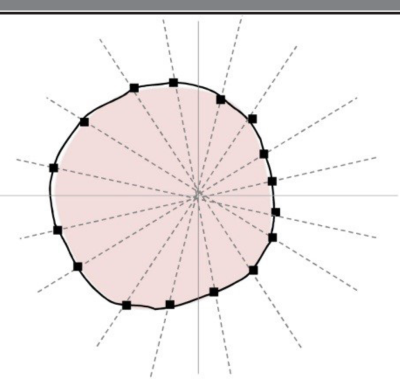
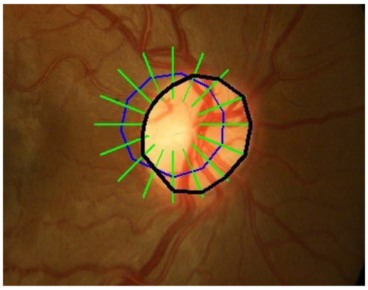


Figure 11 shows an example of a real OD edge adjustment from a retinal image.

Figure 11. Example of the segmentation, (blue) result of the ES, (green) projection lines for *k=16 for l=100pixel*, (black) result of adjustment through projection lines.

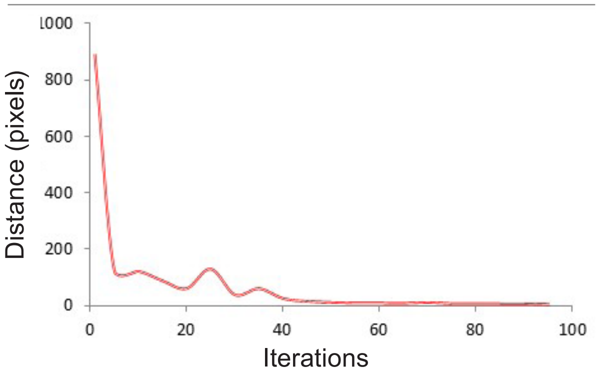


5. RESULTS

The tests were done using implementations of the methods performed using Matlab 2011a. The set of images utilized was made up of 491 images taken from public repositories, DIARECTDB (DIAREDB, 2011) and STARE (STARE, 2011).

The initial experimental tests were aimed at determining the function parameters of the ES. The convergence of the ES was analyzed by estimating the distance from the center of the circumference for the best individual to point *pr*, pre-defined and established manually, located in the center of the OD. **Figure 12** shows the average behavior of a set of twenty executions of the average of the distance between the best individual's solution and *pr*. After 60 iterations, the average stabilizes. However, for some executions, the distance continued to decrease until after more than 80 iterations.

Figure 12. Average behavior of the best individual's distance with the center of the optic disc.



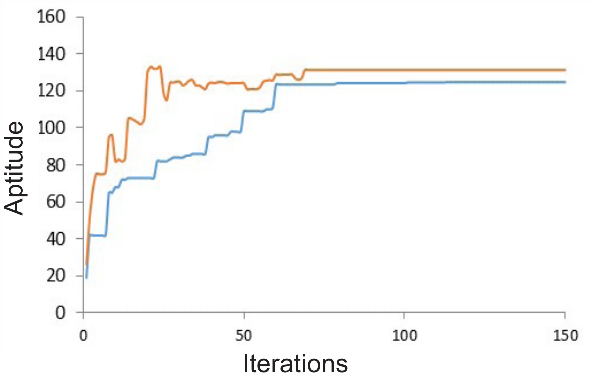
In terms of the initial radius size of the circumferences, it was established through experimentation that a healthy optic disc is represented on average by a circle with a radius equivalent to 100 *pixels* in images with a size of 1500 x 1152 *pixels*. In general, the parameterization of the ES was established according to **Table 1**.

Table 1. Parameters of the proposed method

Localization (ES)		OD Segmentation	
Parameter	Value	k	64
Prob. of Mutation	0,01	*l*	Individual's radius
Prob. of Crossing	10		
Initial Radius	100		
Puntos de evaluación	100		
Max. Generaciones	100		

This parameterization was used to measure efficiency in relation to the aptitude function. **Figure 13** shows the average aptitude behavior or fitness of the best individual and the average aptitude of the population for a group of twenty executions.

Figure 13. Behavior for the best individual's fitness (*blue*) and the average population's fitness (*red*).



Given the difficulty of determining a generalized method for quantifying the precision of techniques proposed for OD localization in retinal images, and because this evaluation is of a subjective nature, represented in the visual valuing of the results, a criterion has been established to determine whether the result of the evolution strategy has generated a correct localization. This criterion considers that if 60% of the area of the circle obtained as a solution from the ES is shared with the OD region established manually, a correct localization is defined. The method was applied to the 491 images, obtaining 95.7% successful localizations and 4.3% erroneous localizations. A set of localizations is shown in **Figure 14**.

After each localization, the method applies the OD segmentation algorithm. This algorithm optimizes the determination of the OD's edge. Complete application of the method proposed allows for an average increase of the overlap area of more than 97% between the solution obtained and the one established manually.

Figure 14. Examples of results of the evolution strategy.

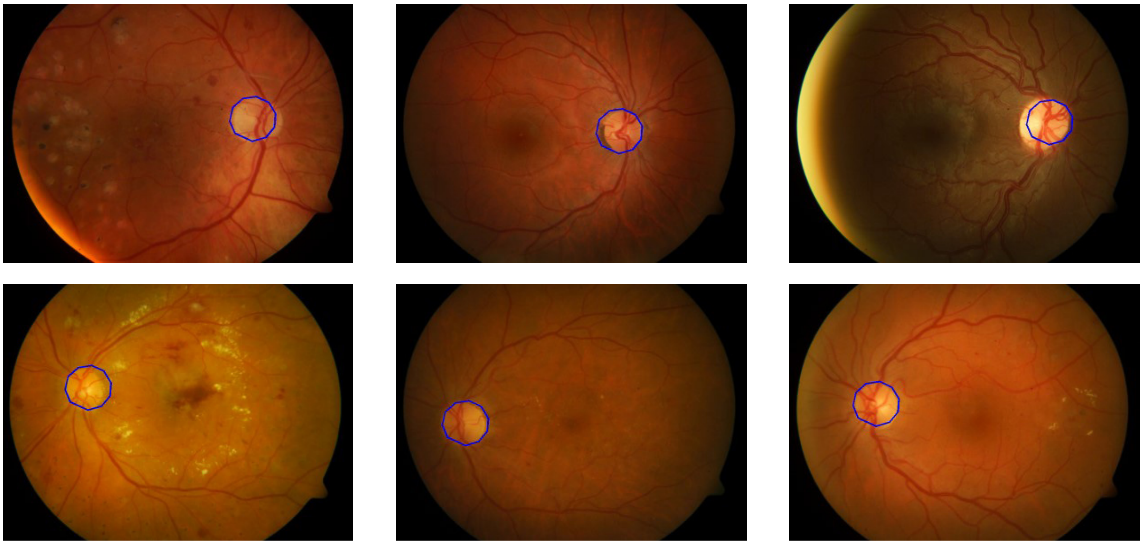


Figure 15. Result of the localization (*blue*) and segmentation of the optic disc (*black*).

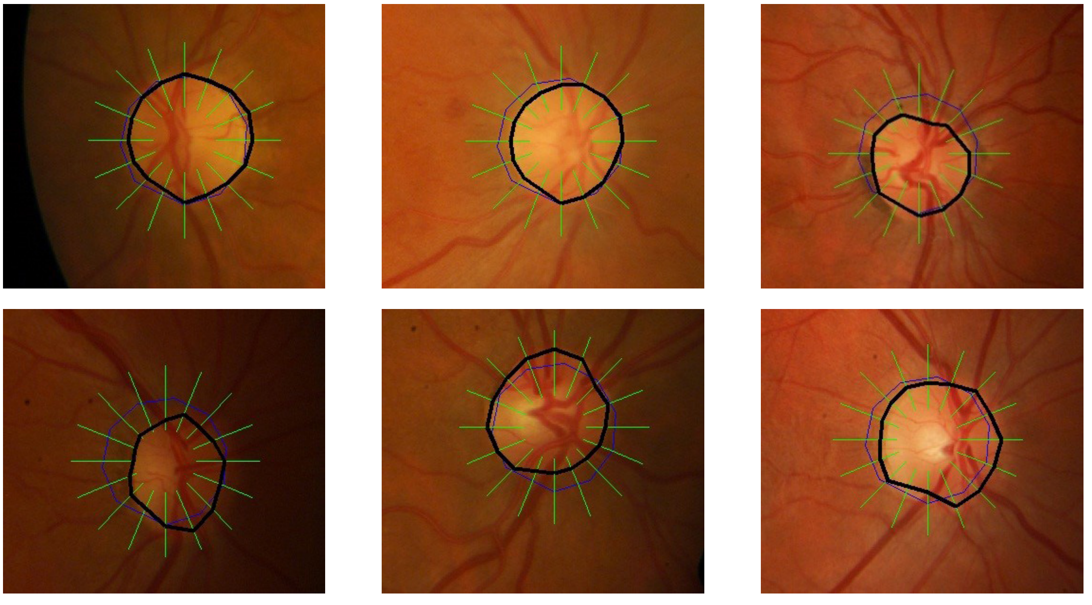


Table 2. Results and comparison of the proposed method.

Method	Images	Precision
Sekhar, et al. (2008)	34	94.4%
Siddalingaswamy, P. and	100	92 %
Gopalakrishna, K. (2009)	100	92%
Usman M. et al. (2010)	680	93.8%
Piñao, J. and Manta C. (2012).	1422	92%
Proposal	461	95.7%

The results of the method's application can be seen in **Figure 15**. **Table 2** shows the results obtained and the comparison with other methods reported in the literature.

6. CONCLUSIONS

The proposed method can locate the optic disc in color retinal images with a precision of nearly 96% in accordance with the results obtained through validation with public repositories. One of the method's main advantages is that it does not require user intervention. The results obtained coincide by 97% with the area of the optic disc.

The factors that intervene in the images in which the algorithm did not obtain a proper localization include the existence of conditions that augment the measurement f_b (x,y,r) of the aptitude function, which quantifies the presence of bright pixels within the image. These conditions are present in images in which the area affected by the presence of exudates occupies a large region within the ocular surface. This is characteristic of patients in advanced stages of the illness. Another important factor is that some images do not show a sufficient contrast between the OD and the rest of the surface. Therefore, a standardization of the technical conditions in the acquisition process is required.

REFERENCES

Canny, J. (1986). A Computational Approach to Edge Detection, *Pattern Analysis and Machine Intelligence, IEEE Transactions*, 8,(6), November, pp. 679-698.

Diarectdb, Download Images Section, DIARECTDB: Standard diabetic retinopathy database. Digital Retinal Images, IMAGERET project. [Online] Available on: http:// http://www2.it.lut.fi/project/imageret/diaretdb1/. [Consulted September 1 2012].

Giancardo, L.; Meriaudeau, F.; Karnowski, T.; Li, Yaqin; Garg, S.; Kenneth W. Tobin Jr. y Chaum, E. (2012). Exudate-based Diabetic Macular Edema Detection in Fundus Images Using Publicly Available Datasets, *Medical Image Analysis*, 16(1), January, pp. 216-226.

Hoover, A. y Goldbaum, M. (2003). Locating the Optic Nerve in a Retinal Image Using the Fuzzy Convergence of the Blood Vessels. *IEEE Transaction on Medical Imaging*, 22(8), August, pp. 951-958.

IDF, International Diabetes Federation. *Diabetes Atlas, 5th edn. Brussels*, Begium: International Diabetes Federation. [Online]: Available on: http://www.idf.org/diabetesatlas. [Consulted November 18 2012].

Lee, S.; Wang, Y. y Lee, E. (1999). A Computer Algorithm for Automated Detection and Quantification of Microaneurysms and Haemorrhages in Color Retinal Images. *SPIE on Image Perception and Performance*, 3663(1), May, pp. 61-67.

Li, H. y Chutatape, O. (2004). Automated Feature Extraction in Color Retinal Images by a Model Based Approach. *Biomedical Engineering, IEEE Transactions on* 51(2), February, pp. 246-254.

Li, H. y Chutatape, O. (2003). A Model-Based Approach for Automated Feature Extractionin Fundus Images. *IEEE International Conference on Computer Vision,* 1(1), pp. 394-399, 2003.

Lowell, J.; Hunter, A.; Steel, D.; Basu, A.; Ryder, R.; Fietcher, E. y Kennedy, L. (2004). Optic Nerve Head Segmentation. *Biomedical Engineering, IEEE Transactions on*, 23(2) February, pp. 256-264.

Lu, S. y Lim, J. H. (2011). Automatic Optic Disc Detection from Retinal Images by a Line Operator. *IEEE Transactions on Biomedical Engineering,* 58(1), pp. 88–94.

Shijian, Lu (2011). Accurate and Efficient Optic Disc Detection and Segmentation by a Circular Transformation. *IEEE Transactions on Medical Imaging,* 30(12), pp. 2126–2133.

Narendra V. y Hareesh K. (2011). Study and Comparison of Various Image Edge Detection Techniques Used in Quality Inspection and Evaluation of Agricultural and Food Products by Computer Vision. *International Journal Agriculture and Biological Engineering*, 4(2) June, pp. 83-90.

Niemeijer, M.; Ginneken, Bv.; Russell, S.; Maria S. A.; Suttorp-Schulten M. S. y Abramoff, M. (2007). Automated Detection and Differentiation of Drusen, Exudates, and Cotton-Wool Spots in Digital Color Fundus Photographs for Diabetic Retinopathy Diagnosis. *Investigative Ophthalmology and Visual Science*, 48(5) March, pp. 2260-2267.

Mahfouz, A. y Fahmy, A. (2010). Fast Localization of the Optic Disc Using Projection of Image Features. *IEEE Transactions on Image Processing,* 19(12), pp. 3285–3289.

Piñao, J. y Manta C. (2012). Fovea and Optic disc Detection in Retinal images with Visible Lesions. *IFIP Advances in Information and Communication Technology*, 372, pp. 543-552.

Qureshi, R.; Kovacs, L.; Harangi, B.; Nagy, B.; Peto, T.; Hajdu, A. (2012). Combining Algorithms for Automatic Detection of Optic Disc and Macula in Fundus Images. *Computer Vision and Image Understanding* 116(1), pp. 138–145.

Siddalingaswamy, P. y Gopalakrishna K. (2009). Automated Detection of optic Disk and Exudate in Retinal Images, 13th International Conference on Biomedical Engineering, 23(1), pp. 277-279.

Sinthanayothin, C.; Boyce, J. F.; Cook, H. L.; y Williamson, T. H. (1999). Automated Localization of the Optic Disc, Fovea, and Retinal Blood Vessels from Digital Colour Fundus Images, *British Journal of Ophthalmology*, 83(8), August, pp. 902–910.

Sinthanayothin, C.; Kongbunkiat, V.; Phoojaruenchanachai, S.; y Singalavanija (2003). A. Automated screening system for diabetic retinopathy. *In Proceedings of the International Symposium on Image and Signal Processing and Analysis (ISPA2003)*, 2(1), pp. 915–920.

Singalavanija, A.; Supokavej, J.; Bamroongsuk, P.; Sinthanayothin, C.; Phoojaruenchanachai, S. y Kongbunkiat, V. (2006). Feasibility Study on Computer-Aided Screening for Diabetic Retinopathy. *Japanese Journal of Ophthalmology*, 50(1), July-August, pp. 361–366.

Stare (2011). Download Images Section, STARE project: Structured Analysis of the Retina, University of California. [Online]: Available on: http:// http://www.parl.clemson.edu/stare/. [Consulted September 1 2012].

Sujithkumar, S. y Vipula, S. (2012). Automatic Detection of Diabetic Retinopathy in Non-dilated RGB Retinal Fundus Images. *International Journal of Computer Applications*, 47(19), June, pp. 26-32.

Usman, M.; Aftab Khan,; Khalid Iqbal,; Wasi Haider Butt. (2010). Retinal Images: Optic Disk Localization and Detection. *Image Analysis and Recognition, Lecture Notes in Computer Science,* 6112, pp. 40-49.

Walter, T.; Klein, J.-C.; Massin, P.; y Erginay, A.; (2002). A Contribution of Image Processing to the Diagnosis of Diabetic Retinopathy-Detection of Exudates in Color Fundus Images of the Human Retina. *Medical Imaging, IEEE Transactions*, 21(10), October, pp. 1236-1243.

TO REFERENCE THIS ARTICLE / PARA CITAR ESTE ARTÍCULO / PARA CITAR ESTE ARTIGO /

Sánchez-Torres, G.; Espinosa-Bedoya, A.; Ceballos, Y. F. (2014). Optic Disc Detection in Retinal Images using an Evolution Strategy ($\mu+\lambda$). *Revista EIA*, 11 (21) January-June, pp. 53-63. [Online]. Available on: http://dx.doi.org/10.14508/reia.2014.11.21.55-66