# Genetic Search for Face Detection

Md. Al-Amin Bhuiyan and Fawaz Waselallah Alsaade

*Abstract*— **Genetic Algorithms have attained overwhelming attention in successfully solving many computer vision problems. This paper addresses a robust face detection method with images in diversified backgrounds employing genetic algorithm. The system is organized with skin color segmentation in YCbCr color space. Since the computational cost for genetic algorithm is extremely high, the searching zone for probable face area is limited to skin color region so that the required processing time has been greatly reduced. The efficacy of this system has been verified over experimental procedures which reveal that the proposed face detector implements better than existing methods in terms of success rate and capability of allowing dissimilar illumination condition.**

*Index Terms*—**Face detection, genetic algorithm, roulette wheel selection, cross-over, mutation**

## I. INTRODUCTION

GENETIC Algorithms (GAs) belong to randomized search methods that employ processes found in natural biological evolution. They work on populations of individuals, allowing for parallel processing to be performed to optimize the problem. The GAs have been implemented to solve a diversity of problems related to image processing, pattern recognition, computer vision, fingerprint matching, human-machine interface, surveillance systems, forensic applications, and so on.

A fair amount of works have been published in literature on various approaches of face detection [1-3]. Most popular methods employed for face detection are: neural networks [1], eigenface based principal component analysis [4], deformable template [5], skin color analysis [6]. S.Z. Li and Z. Zhang have employed a backtrack technique for learning a boosted classifier and developed a floatboost algorithm for face detection [7]. W. Freeman, E. Pasztor have proposed a model based approach using Marcov network and Bayesian belief propagation for learning network parameters from examples [8], but its main limitation is that it requires initial location of the face to be known. C. Lin has developed a face detection scheme based on YCbCr color model and neural network based approaches [9]. Rowley et. al [1] proposed a bootstrap method to develop a neural network-based upright frontal face detection system, which needs a huge quantity of face and non-face training examples. Sung and Poggio [10] have proposed an example-based method for face detection. Since this system is established for frontal view faces, facial images at other alignments are difficult to identify.

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This paper addresses a face detection scheme employing a two folds approach: (i) skin color extraction and (ii) genetic searching. The system is organized with approximate localization of the face region by thresholding the image using skin color dissection. The exact position of the face is determined using genetic algorithm in the grayscale mode. Experimental results imply that the method is skillful in detecting faces from intricate backgrounds in a variation with illumination, expression and pose.

The rest of the paper is organized as follows. Section II highlights the system architecture where contrast equalization, median filtering and skin color segmentation are briefly described. Section III illustrates genetic searching strategy. Section IV presents the experimental investigations and results. Section V draws the overall conclusions of this paper.

## II. SYSTEM ARCHITECTURE

Face detection is concerned with localizing image areas consistent to human faces. The system proposed in this research employs color and shape information to localize face regions. The overall system architecture is illustrated in Fig. 1.

### A. Contrast Equalization

The original images in the face databases are color images with different lighting conditions. Some of the images contain very poor contrast as they are captured in indoor or cloudy environments. Therefore, to make the images contrast invariant regarding bright or dark lighting conditions, if these are handled with same rms (root mean square) contrast. The rms contrast metric [11,12] is given by:

$$\left.\begin{array}{l} C_{r,rms} = \left[ \dfrac{1}{MN} \sum\limits_{i=0}^{M-1} \sum\limits_{j=0}^{N-1} (r(i,j) - \bar{r})^2 \right]^{\frac{1}{2}} \\[2em] C_{g,rms} = \left[ \dfrac{1}{MN} \sum\limits_{i=0}^{M-1} \sum\limits_{j=0}^{N-1} (g(i,j) - \bar{g})^2 \right]^{\frac{1}{2}} \\[2em] C_{b,rms} = \left[ \dfrac{1}{MN} \sum\limits_{i=0}^{M-1} \sum\limits_{j=0}^{N-1} (b(i,j) - \bar{b})^2 \right]^{\frac{1}{2}} \end{array}\right\} \quad (1)$$

where $r(i,j)$, $g(i,j)$, $b(i,j)$ are the brightness due to red, green, and blue color components, respectively, and $\bar{r}$, $\bar{g}$, $\bar{b}$ are the mean illuminations due to red, green, and blue color components. All images are kept the same illumination and same rms contrast by applying the following expressions:

$$\mathbf{f}_r = \alpha_r \, \mathbf{C}_r + \beta_r, \quad \mathbf{f}_g = \alpha_g \, \mathbf{C}_g + \beta_g, \quad \mathbf{f}_b = \alpha_b \, \mathbf{C}_b + \beta_b \quad (2)$$
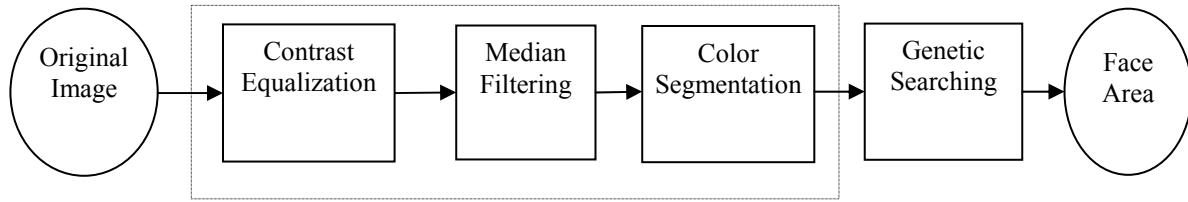
Fig. 1.  System architecture for face detection process.



(a)  Images with different brightness and contrast



(b) Images with same brightness and same rms contrast

Fig. 2.  Illumination and rms contrast equalization

where $\alpha_r$, $\alpha_g$, $\alpha_b$, denote the contrast due to red, green, and blue color components, respectively, and $\beta_r$, $\beta_g$, $\beta_b$ represent the amount of brightness needed to be added to or reduced from the respective red, green, and blue components $C_r$, $C_g$, $C_b$ of the original color image $C$ to the new color image $f$. The illumination and rms contrast equalization process for color images is shown in Fig. 2.

### B. Median Filtering

Images are usually encountered by different types of noise. The fine details of the image correspond to high frequencies which merge with noise. Therefore, median filter is employed to eliminate the noise.

### C. Skin Color Segmentation

Since the RGB color space is extremely sensitive to illumination changes, many color models have been justified for color segmentation. The YCbCr color model has been selected for this investigation after performing numerous judgments on RGB, HSV, HIS, YIQ color models. The Y in YcbCr represents the luminance component, and Cb and Cr describes the chrominance factors.

This research uses YCbCr color space for color segmentation due to the following four folds reasons:

(i)   Using YCbCr color model, it is possible to eliminate the variation of luminance component caused by the illumination environments.

(ii)  The YCbCr is widely employed in digital video coding applications.

(iii) The skin color cluster is more compact in YcbCr than other color model.

(iv)  YcbCr has the shortest overlap between skin and non-skin information under diversified lighting environments.

The transformation from RGB to $YC_bC_r$ is expressed by the following equations [3]:

$$\begin{bmatrix} Y \\ Cb \\ Cr \end{bmatrix} = \begin{bmatrix} 0.299 & 0.587 & 0.114 \\ -0.169 & -0.331 & 0.500 \\ 0.500 & -0.419 & -0.081 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (3)$$

where $R,G,B$ represent the red, green, and blue color components existing in the range [0,255]. Since the skin-colors are clustered in YcbCr color model and differ from person to person and of different races, the pixels are clustered into skin pixels and non-skin pixels. The most appropriate measures that has been found for all input images in databases are: $C_b$ in [77,127] and $C_r$ in [139,210]. Let a color image $C(i,j)$ consists of three color channels $C(i,j) = (C_R(i,j), C_G(i,j),\ C_B(x,y))$, at $(i,j)$ of size $M \times N$. A pixel $P$ at coordinates $(i,j)$ has the YCbCr values $P(i,j) = (Y(i,j), Cb(i,j), Cr(i,j))$, or $P = (Y, Cb, Cr)$ be mapped into a gray level $n = f(x,y) \in [0,L]$. The skin color segmentation is accomplished according to the following transformation function:

$$n = \begin{cases} m = (C_R + C_G + C_B)/3, \\ \quad \text{when } 77 \le C_b \le 127 \; \&\& \; 139 \le C_r \le 210 \\ 0, \quad \text{otherwise} \end{cases} \quad (4)$$

where $m$ and $n$ denote the gray levels at point $\mathbf{P}(i,j)$ and the transformed pixel $f(i,j)$, respectively. Fig. 3 illustrates the transformation operation.

The detection of skin color regions by the segmentation process is shown in Fig. 4. The exact location of the face is obtained from the image employing genetic algorithm.
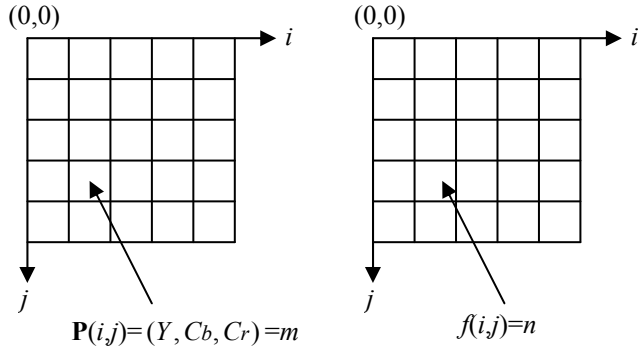


Fig. 3.  Color segmentation operation.



(a) Original image      (b) Skin colors replaced by grayscale

Fig. 4.  Skin color segmentation.

## III. GENETIC SEARCHING

GA is a randomized search technique that employs mechanisms of natural selection and genetics to imitate the performance of biological systems. The searching process commences on a set of population, each signifying a probable solution to the given problem. The fundamental followed in face detection process using genetic algorithm is shown by a flowchart in Fig. 5.

First, a template of the face image acquired by averaging the gray levels of pixels of a number of face images is constructed. Then the template image is moved through the whole image randomly at different locations to find the position where the most appropriate similarity is found [4]. This research employs genetic algorithm for the optimization of five parameters: center of the template, scaling and rotation of the template, and matching rate between the input image and the template image.

### A. Chromosome Representation

In GA, it is necessary to represent each chromosome in the population set. The chromosome representation defines how the problem is organized in the algorithm. Each chromosome is characterized by a binary string consisting of the set {0,1} of length $N$. A chromosome consists of five optimization parameters, $\{\mathbf{P}_i, i = 0,1, \ldots, 4\}$ corresponding

to the $x$-and $y$-coordinates of the center of the template image $tx$ and $ty$, scaling factor of the template ($s=sx=sy$), rotation of the template ($\theta$), and matching rate between the input image and the template image ($m$), respectively, each consisting of 8-bit length. The range of the parameters chosen for this research are: $0.8 \le s \le 1.2$, $-30\degree \le \theta \le 30\degree$, $-50 \le t_x \le 50$, $-50 \le t_y \le 50$, $0.8 \le m \le 1$, respectively.

A population with a set of chromosomes is determined by the strings as: $\{\mathbf{C}_j, j = 0,1, \ldots, M - 1\}$, where $M$ is the number of the chromosomes or the population size.

### B. Fitness Function

The fitness function is employed to express a fitness value to each possible solution. It identifies the best individual during the evolutionary process. The fitness of a chromosome at a particular location of the image is defined as a function of the difference between the intensity value of the input image and that of the template image [3]. Thus for each chromosome $k$, the fitness function is defined as:

$$f(k) = 1 - \frac{\underset{(i,j) \in W}{\Sigma} \left| f(i,j) - f_{k,t}(i,j) \right|}{I_{max} \times M \times N} \quad (5)$$

where $I_{max}$ is the maximum illumination of the image, $M$ and $N$ denote the rows and columns of the template image, $f$ and $f_{k,t}$ are intensity values of the original image and the template image when it is computed for the $k$-th location of the chromosome, respectively.

### C. Selection

The selection process picks out the 'survival of the fittest' chromosomes from the mating pool that provide their gene-inherited knowledge to breed for the next generation according to their fitness function. This research employs roulette-wheel selection process. The probability $p_k$ of the survival of the $k$-th selected chromosome is given by the expression:

$$p_k = \frac{f(k)}{\overset{N}{\underset{i=1}{\Sigma}} f(k)} \quad (6)$$

where $N$ is the size of the population and $f(k)$ is the fitness of the $k$-th chromosome.

### D. Crossover

Crossover is a probabilistic process where two parent chromosomes interact with each other and produce a pair of offspring. The main objective of the crossover operation is to generate the diversified and possibly fittest new chromosomes. The cross-over operator selects randomly a verge point where two parent chromosomes exchanges their information. If a pair of chromosomes does not make cross over, the chromosome cloning occurs. In this experiment, the crossover rate was selected adaptively [13]. Let $f_{max}$ be the maximum fitness value of the current population, $f_\mu$ be the average fitness value of the population and $f_L$ be the

larger of the fitness of the individual to be crossed. Then the probability of crossover $p_c$ is expressed by the equation:

$$p_c = t_1 \times \frac{f_{\max} - f_L}{f_{\max} - f_\mu} \qquad if\ f_L > f_\mu,$$

$$p_c = t_2 \qquad if\ f_L \leq f_\mu, \qquad (7)$$

where the values of $t_1$ and $t_2$ are chosen as 1.0 and 0.7, respectively.

### E. Mutation

Mutation characterizes an alteration in the gene and supports in avoiding loss of genetic diversity. Its role is to offer an assurance that the search algorithm is not stuck on local optimum problem.

Mutation arbitrarily changes one or more genes of a designated chromosome with a probability equal to the mutation rate, $p_M$. The mutation rate for this investigation

was taken adaptively [13]. The mutation probability is expressed by equation:

$$p_m = t_3 \times \frac{f_{\max} - f}{f_{\max} - f_\mu} \qquad if\ f > f_\mu,$$

$$p_c = t_4 \qquad if\ f \leq f_\mu, \qquad (8)$$

where the values of $t_3$ and $t_4$ are chosen as 0.05 and 0.01, respectively; $f_{\max}$ and $f_\mu$ are the same as defined in Eq. [7], and $f$ is the fitness of the chromosome under mutation.

### F. Termination Criterion

The termination condition decides the duration of the learning time and determines how good the solution is for the face detection. This research fixed the termination criterion on: (i) maximum generations to be 300, and (ii) terminate if the fitness value of the fittest chromosome is greater than some threshold value.
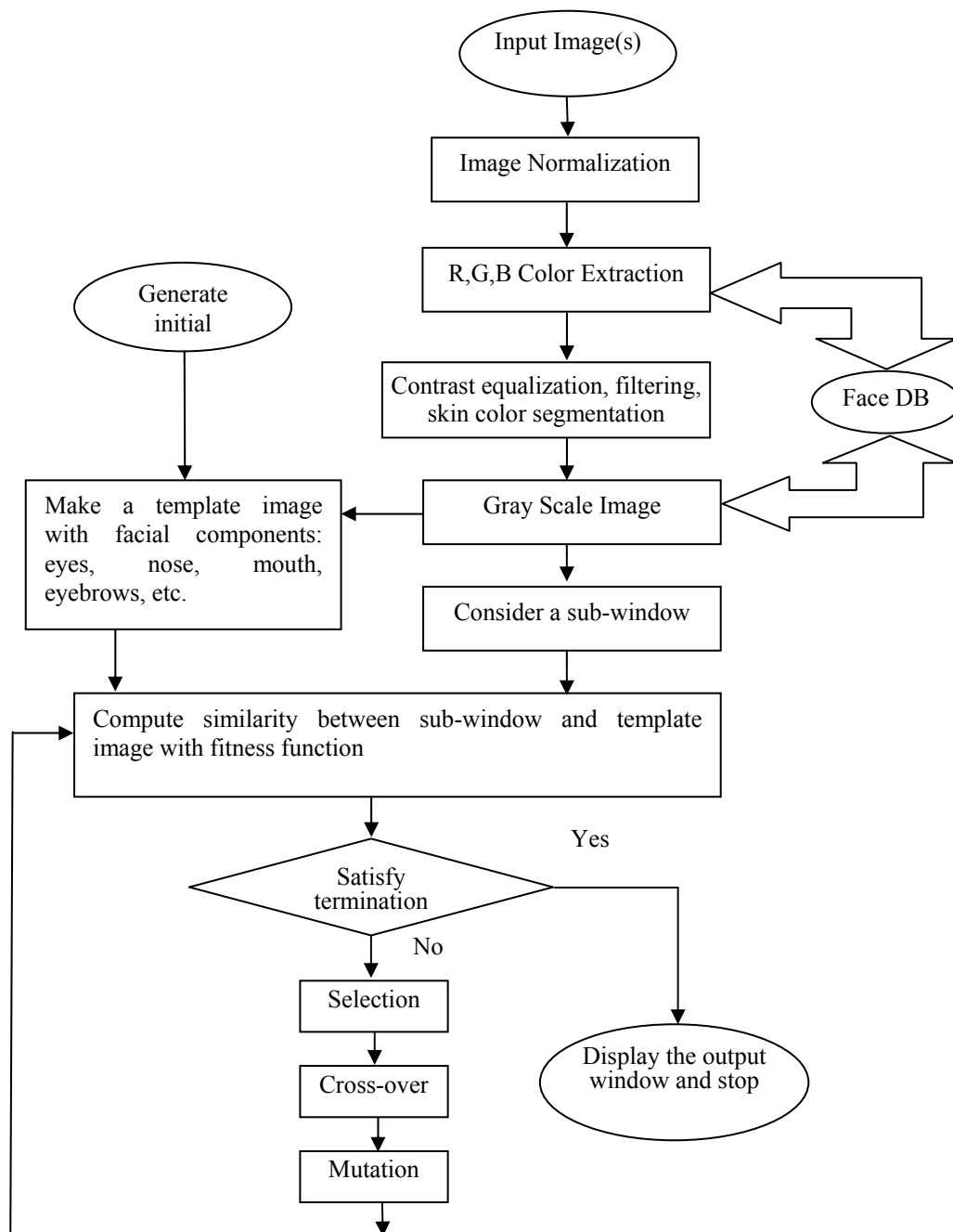
Fig. 5. Flowchart for face detection using genetic algorithm.

## IV. EXPERIMENTAL INVESTIGATIONS AND RESULTS

The effectiveness of this approach has been justified over several experiments using an image database with various kinds of facial expressions. Experiments have been carried out on an Intel® Core™ i3-3110M CPU with 2.40 GHz Laptop. The system has been implemented by Visual C++.

The method has been tested on BioID database, which contains grayscale, frontal facial images of dimensions 384×286, acquired under various lighting conditions in a complex background. The database contains tilted and rotated faces, in a few cases people were wearing eyeglasses and had their eyes shut or pose with various expressions. When a complex image is subjected in the input, the face detection result highlights the facial part of the image, as shown in Fig. 6.

The genetic algorithm has been studied under single point cross-over with different size of populations. The fitness versus generation graph is shown in Fig. 7, which indicates that the larger population size performs better due to the fact that larger pool of wide schemata existing in the chromosome but the inertia of larger population also creates a problem of worse start. Smaller population size, on the contrary, has the capability of fluctuating more quickly and thus show better starting on-line performance. So a trade off is always considered between population size and the mode of cross-over. So we embraced single point cross-over with a population size of 150 during face detection process.



Fig. 6. Face detection results for the persons at BioID image database:-(a10): original image, and (b1)-(b10): detected face image.
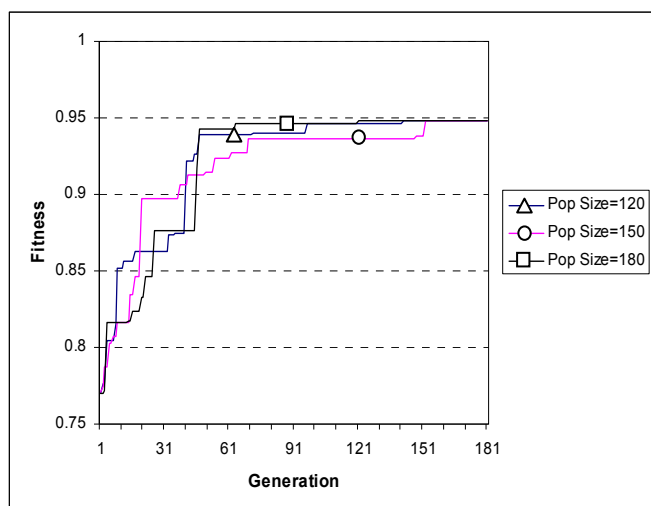
Fig. 7. Fitness versus generation (single point cross-over).

## V. CONCLUSION

This article addresses the employment of genetic algorithm to search for the face of a male or female in a two-dimensional color and gray scale images. Although the human beings achieve these jobs innumerable times a day, they are still inspiring job for computer vision. Most of the researchers consider this sort of problem at frontal view faces with normal expression and normal illumination environments. The efficacy of this face detection method has been verified both in simple and intricate backgrounds for different types of face and non-face images of different resolutions. The algorithm is capable of detecting the faces in the images with diversified backgrounds and lighting environments. Our next approach is to expand the system for overlapping faces and develop an eye tracking system that will be able to detect an eye in a face image and implement the gaze direction to instruct the social robots for human-robot interaction.

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