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Robust Face Detection using Genetic Algorithm

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Abstract: This research presents a robust and precise scheme for detecting faces and locating the facial features in images with complex backgrounds using genetic algorithm. The system is based on visual information of the face from the template image and is commenced with the estimation of the face area in a given image. Facial features, such as eyes, nose, mouth, eyebrow, etc. are then localized from face skeleton with the knowledge of the face geometry. Experimental results demonstrate that this face detector provides successful results for the images of individuals which contain quite a high degree of variability in expression, pose and facial details.

Key words: Face detection, facial features, genetic algorithm, cross-over, mutation, roulette wheel selection

INTRODUCTION

Genetic Algorithms (GAs) belong to a class of stochastic search method represented by natural population genetics. They perform a highly parallel adaptive search process. The GAs have been employed in a wide variety of problems related to pattern recognition, image processing, medical image registration, image segmentation, contour recognition and so on. This paper investigates the application of genetic algorithm to search for the face of a particular individual in a two-dimensional gray scale image.

The problem of detecting the faces and facial features in image sequences has become a popular area of research due to its emerging applications in human-computer interface, surveillance systems, secure access control, video conferencing, financial transaction, forensic applications, pedestrian detection, driver alertness monitoring systems, image database management system and so on.

Various approaches to face detection and facial feature extraction have been reported in literature over the last few decades, ranging from the geometrical description of salient facial features to the expansion of digitized images of the face on appropriate basis of images, Low and Kee (2001). Different techniques have been introduced recently, for example, principal component analysis Turk and Pentland (1991), neural networks, Rowley *et al.* (1998), color analysis, Bhuiyan *et al.* (2003) and so on. Face detectors based on Markov random fields and Markov chains, Freeman *et al.* (2000), make use of the spatial arrangement of pixel gray values. Model based approaches, Yow and Cipolla (1996), Lin and Lin (1996) and Bhuiyan and Hama (2002), assume that the initial location of the face is known. Color based approaches reduce the search space in face detection algorithm. The neural network-based approaches require a large number of face and non-face training examples and are designed primarily to locate frontal faces in grayscale images.

This research explores a face detection system which integrates the detection of human faces in complex backgrounds and localization of facial features such as eyes, nose, mouth, eye-brow, etc. on it. Face detection is established by employing genetic algorithm in the grayscaled image of the face area. Facial features are then detected and localized by the geometrical analysis of the facial skeleton. Experimental results indicate that the system is capable of detecting and locating the face parts from complex backgrounds with a high degree of variability in expression, pose and facial details.

FACE DETECTION METHODOLOGY

Face detection is concerned with determining which part of an image contains face. This is the first step of face recognition which requires both high and low-level visual and geometric information processing. This study presents genetic searching for detecting human faces in

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a complex background. Face detection is achieved by employing template matching between a known face image and the input image. The main steps employed for the face detection process is shown in Fig. 1.

PREPROCESSING

The original image is obviously a color image. It is first converted into gray scale image. While registering images, the eyes, tip of the nose and the corners of the mouth of each face is labeled. These points are then used to normalize each face to same scale, orientation and position. The normalization is performed by mapping the facial features to some fixed locations in an $M \times N$ image. Each normalized image is then subjected to some image processing operations to account for different lighting conditions and contrast.

IMAGE ENHANCEMENT

The face images may be of poor contrast because of the limitations of the lighting conditions. So histogram equalization is used to compensate for the lighting conditions and improve the contrast of the image, Wang and Tan (1999). Let the histogram $h(r_i) = P_i/n$ of a digital face image consists of the color bins in the range [0, C-1], where r_i is the i-th color bin, P_i is the number of pixels in the image with that color bin and n is the total number of pixels in the image. For any r in the interval [0,1], the cumulative sum of the bins provides with some scaling constant. Histogram equalization is performed by transforming the function $s = T(r)$, which produces the mapping with the allowed range of pixel values, i.e., a level s for every pixel value r in the original image and $0 \leq T(r) \leq 1$ for $0 \leq r \leq 1$, as shown in Fig. 2.

FILTERING

Various sources of noise may exist in the input image. The fine details of the image represent high frequencies which mix up with those of noise. So low-pass filters are used to obliterate some details in the image. In this experiment, Prewitt filter is used to suppress the noise.

GENETIC SEARCHING

The Genetic Algorithm (GA) is a stochastic search method based on the mechanics of natural selection and genetics analogous to natural evolution. Central to the idea of GA is a population of individuals, each representing a possible solution to the given problem. Each individual, known as chromosome (usually represented by a bit string consisting of 0s and 1s), is assigned to a fitness value based on how good their solution to the problem is. The individuals then evolve through successive iterations called generations. During one generation, highly fit individuals are given the opportunity to mate with other individuals in the population. Since the least fit individual in the population are less likely to get selected for mating, they disappear from future generations. As a result, the population of individuals converges to an optimal solution to the problem. GAs are robust and can deal successfully with a wide range of problem areas, including those which are difficult for other methods to solve.

To apply GA for face detection, a template of the face image obtained from averaging the gradation level of pixels of a number of similar looking face images of several persons is constructed. The template face image is then moved through the whole image to find the location where the most suitable match exists. This process applies GA

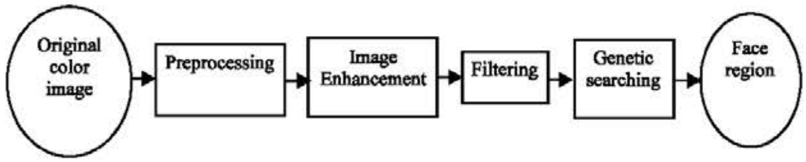

Fig. 1: Fundamental steps employed for face detection

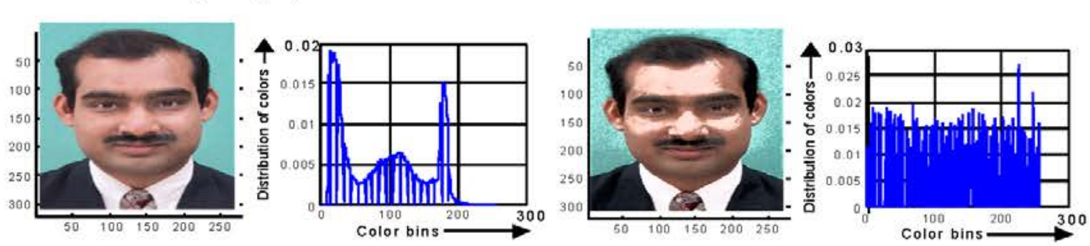

Fig. 2: Histogram equalization of a face image

for the optimization of five parameters such as, center position of the template image, scaling of the template, rotation of the template and matching rate between the input image and the template image. The genetic algorithm and different genetic operations are given bellow.

The algorithm starts with an initial set of random solutions called the population. Each individual in the population, known as chromosome, represents a particular solution of the problem. Each chromosome is assigned a fitness value depending on how good its solution to the problem is. After fitness allotment, the natural selection is executed and the 'survival of the fittest chromosome' can prepare to breed for the next generation. A new population is then generated by means of genetic operations: cross-over and mutation. This evolution process is iterated until a near-optimal solution is obtained or a given number of generations is reached. However, different steps employed in the genetic algorithm for face detection scheme is shown in Fig. 3.

FITNESS FUNCTION

In order to identify the best individual during the evolutionary process, a function needs to assign a degree of fitness to each chromosome in every generation. So in order to determine whether the assumed region of the input image is a face or not, the fitness value of the possible face region is computed by means of intensity similarity.

The fitness of a chromosome is defined as the function of the difference between the intensity value of the input image and that of the template image measured for the expected location of the chromosome. That is, for each chromosome n, fitness function is defined as:

$$f(n) = 1 - \frac{\sum_{(x,y)\in W} \left| f(x,y) - f_{n,t}(x,y) \right|}{B_{max} \times xSize \times ySize} \tag{1}$$

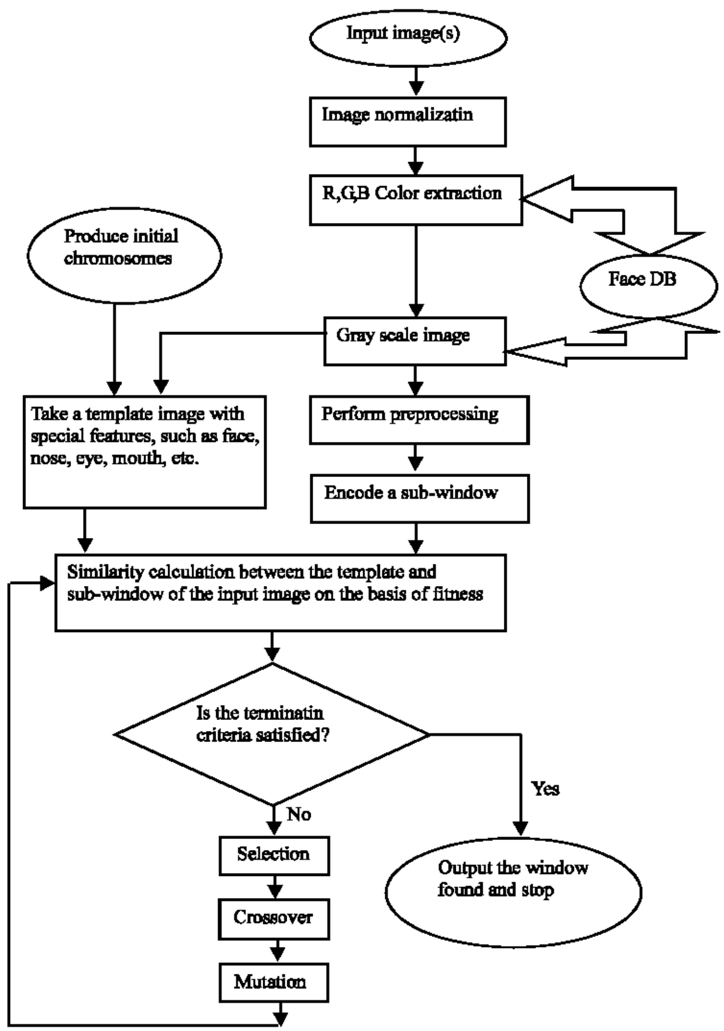

Fig. 3: Flowchart of the genetic algorithm based face detection process

where B_{max} is the maximum brightness of the image, xSize and ySize are the number of pixels in the horizontal and vertical directions of the template image, f and $f_{n,t}$ are the intensity values of the original image and the template image when it is justified for the n-th position of the chromosome, respectively.

SELECTION

Selection operator is a process in which chromosomes are selected into a mating pool according to their fitness function. Good chromosomes that contribute their gene-inherited knowledge to breed for the next generation are chosen. Here we use conventional elitist selection scheme to select an elitist chromosome with the highest fitness value, which is copied directly into the new population of next generation. The other chromosomes are selected by a roulette-wheel selection process, where the selection probability of each individual is proportional to its fitness value.

CROSS-OVER

This operator randomly chooses a crossover point where two parent chromosomes break and then exchanges the chromosome parts after that point. As a result, two offspring are generated by combining the partial features of two chromosomes. If a pair of chromosomes does not cross over, then the chromosome cloning takes place and the offspring are created as exact copies of each parent. Here we have studied single point cross-over, two point cross-over and uniform cross-over operators. The cutting points are selected randomly within the chromosome for exchanging the contents. In this experiment, the cross-over rate was chosen as 0.7 for all cases.

MUTATION

Mutation, which is rare in nature, represents a change in the gene and aids us in avoiding loss of genetic diversity. Its role is to provide a guarantee that the search algorithm is not trapped on a local optimum.

This operator alters a randomly selected gene of chromosome with a very low probability, P_M. For each chromosome, generate a random value between [0,1]. If the random value is less than P_M, then choose a bit at a random location to flip its value from 0 to 1, or 1 to 0. The mutation rate for our method was chosen as 0.01.

The fundamental steps employed for the genetic algorithm are as follows:

Step 1: Initialization: Generate randomly a population of chromosomes of size N: $x_1, x_2, \ldots, x_N$. Assign the crossover probability P_c and the mutation probability P_M.

Step 2: Evaluation: Evaluate the fitness function to measure the performance or fitness for individual chromosome in the population. The fitness function establishes the basis for selecting chromosomes that will be mated during reproduction.

Step 3: Selection: Select a pair of chromosomes for mating. Use the roulette wheel selection procedure, where each chromosome is given a slice of a circular roulette wheel. The area of the slice within the wheel is equal to the chromosome fitness ratio. Obviously, the highly fit chromosomes occupy the largest areas, where the chromosomes with least fit have much smaller segments in the wheel. To select a chromosome for mating, a random number is generated in the interval [0,100] and the chromosome whose segment spans the random number is selected.

Step 4: Cross-over: Produce two off-springs from two parent chromosomes. With the cross-over probability P_c, exchange parts of the two selected chromosomes and create two offspring.

Step 5: Mutation: Apply the conventional mutation operation to the population with a mutation rate P_M. With this mutation probability, randomly change the gene values in the two offspring chromosomes.

Step 6: Termination test: If a predefined termination condition is satisfied, go to Step 7, else go to Step 2.

Step 7: Preservation: Keep the best chromosome.

Step 8: End.

On processing the genetic operation, the face area is detected on the image. The exact locations of the facial features are then searched. Six facial features are localized in this experiment. These are the left and right pairs of eyes, eyebrows, tip of the nose and the center of the mouth. Facial features are extracted from the face profile depending on their geometrical arrangement on the facial skeleton.

EXPERIMENTAL INVESTIGATIONS AND RESULTS

The effectiveness and robustness of the algorithm is justified using different images with various kinds of expressions. Experiments are carried out on a Pentium III 900 MHz PC with 256 MB RAM. The algorithm has been implemented using Visual C++. When a complex image is subjected in the input, the face detection result highlights the facial part of the image, as shown in Fig. 4. The system can also cope with the problem of partial occlusion of

(a01) (b01) (a02) b02) (a03) (b03)

Fig. 4: Face detection for the persons at their work places: (a01)-(a03): original image and (b01)-(b03): detected face image

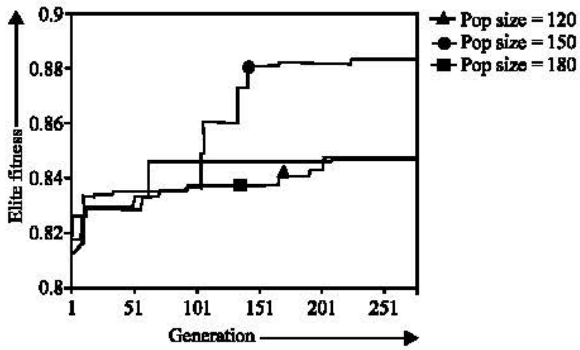

Fig. 5: Elite fitness versus generation (Single point cross-over)

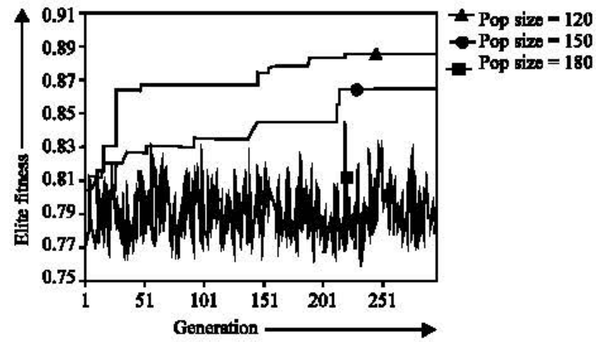

Fig. 6: Elite fitness versus generation (Uniform cross-over)

mouth and wearing sunglasses Images of different persons are taken at their own work places and at different environments both in shiny and gloomy weather. Most of the images are taken using a digital camera, but some are from scanner and some from video tapes recorded from different television channels. The algorithm is capable of detecting single face in an image. For multiple faces, the system finds the dominant face only. A total of 150 images, including more than 80 different persons, are used to investigate the capacity of the proposed algorithm. Among them only 2 faces are found false. Experimental results demonstrate that the success rate of approximately 99% $\left(\frac{153}{155}\times 100\% = 98.71\%\right)$ is achieved. The main reason behind the failure of those images in finding face regions is the occlusion.

Face detection is performed by using both color and grayscale modes and facial features are extracted in grayscale mode. The existence of facial features like eyes, nose, mouth and so on are the evidences that the candidate region is indeed a face. The genetic algorithm is examined using single point and uniform cross-over with different population size and the results are shown in Fig. 5 and 6.

Figure 5 reveals that larger population size offer better performance because of the larger pool of diverse schemata available in the chromosome but the inertia of larger population also boils down a problem of poorer initial. Smaller population size, on the contrary, have the ability to change more rapidly and thus exhibit better initial on-line performance. Figure 6 shows that smaller population size is better for uniform cross-over, whereas larger population size suffers from fluctuations. So a trade off is always taken between population size and the way of cross-over. Therefore, we adopt single point cross-over with a population size of 150 during face detection and facial feature extraction process.

CONCLUSION

Detection of human faces is a problem that appears time. This task, which seems effortless for humans, does not lend itself easily to computational approaches. Though human beings accomplish these tasks countless times a day, they are still very challenging for machine vision. Most of the researchers attack this kind of problem with face localization and feature selection with frontal view faces and without facial expression and normal lighting conditions although the variation between the images of the same face is too large due to facial expression, hair style, pose variation, lighting conditions, make-up, etc. In this study, face detection has been implemented using genetic algorithm to search for the face of a particular individual in an image. The effectiveness of the face detection algorithm has been tested both in simple and complex backgrounds for different types of face and non-face images of 320×240 resolution. The algorithm is capable of detecting the faces in the images with different backgrounds and lighting conditions. Our next approach is to extend the algorithm for multi-face detection and overlapping faces in images and to detect facial poses and develop a gaze estimation algorithm that will be able to detect an eye in a face image and estimate the gaze direction. Our main target is to instruct operations to robots and make them understand the human's intentions and interests over facial expressions so that they would be capable of grasping with more intelligence while working cooperatively with human beings.

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