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A PATH FOR HORIZING YOUR INNOVATIVE WORK

FACE DETECTION USING PSO TEMPLATE SELECTION

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Abstract: In this work we present a new method based on PSO (particle swarm optimization) to optimize templates for frontal face detection. In the past, several methods for face detection have been developed using face templates. These templates are based on common face features such as eyebrows, nose and mouth. Templates have been applied to a directional image containing faces computing a line integral to detect faces with high accuracy. In this paper, the PSO is used to select new templates optimizing its size and response to a face in the directional image. The method was tested on a data base composed of two video sequences and compared to the results of the traditional anthropometric templates that contain features from the eyebrow, nose and mouth. Results show that templates selected by PSO have significant better performance in the estimation of face size and the line integral value. In both sequences face detection reached 99% and 100%. The templates have fewer number of points compared to the traditional anthropometric templates which will lead to lower processing time.

Keywords: Face recognition, Eigenfaces, PCA, SIFT, Keypoint Descriptor.

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INTRODUCTION

Face detection in digital images employing templates has been approached in several previous studies [5], [6], [7],[8], [9]. In these studies face detection is performed using two stages: coarse face detection and fine face detection. In the coarse face detection stage the possible face center is determined using elliptical templates based on Hough transform over a coarse directional image [5]. The highest value in the accumulator is taken as the possible face center. The fine face detection is performed in a region around the coarse face center. For this purpose a set of face templates are used to compute a line integral of each template over the directional image [3].

The set of templates include different face size and have the following face features: eye brows, nose, mouse and lower part of the chin. These templates are called anthropometric templates because they include key features of the face. Although, the results of this method are good especially in real time applications, it has not been demonstrated that these templates are the optimum for the line integral computation. Therefore, a natural next step would be to develop a method to find better templates that could improve the results of this method.

In this paper, we use the PSO (Particle Swarm Optimization) algorithm to search for new templates. The PSO algorithm was originally introduced by Eberhart and Kennedy [4]. Several papers have expanded the original algorithm and analyzed the convergence and stability [1],[10], [11], [12], [13], [14]. A parameter called inertia has been proposed with good results [11].

LITERATURE REVIEW

Face detection and recognition technology [5, 8] has been widely discussed in relation to computer vision and pattern recognition. Numerous different techniques have been developed owing to the growing number of real world applications. For service robot, face detection and recognition are extremely important, in which the emphasis must be put on security, real-time, high ratio of detection and recognition. For real-time face detection, typically, in 1997, P.Viola presented a machine learning approach based on Adaboost and Cascade algorithm, which is capable of detecting faces in images in real-time [9]. Based on this work, many researchers begin to study on Boosting algorithm. Stan Z. Li proposed a multi-view face detection algorithm based on FloatBoost [11]. Then P.Viola presented an asymmetric Adaboost algorithm which can be used for fast image retrieval and face detection.

For face recognition, the eigen face approach was presented byTurk and Pentland introduced in [3]. This approach is based on PCA, which was later refined by Belhumeur et al. [12] and Frey et al. [13].However, most of the methods above are based on 2D face image and are easily affected by changeable factors such as pose, illumination, expression, makeup and age. In order to overcome these problems, 3D face detection and recognition methods have been developed rapidly in recent years [6].

Bronstein et al. presented a recognition framework based on3D geometric invariants the human face [14]. Wang et al. described a real-time algorithm based on fisherfaces [10]. Though these 3D methods which emphasis on the shape of human face are robust in variable environment, they overlook the texture information of human face on the contrary. Therefore, in order to get better efficiency, face data should be sufficiently used and both 2D and 3D face information should be considered [1-3].

Face detection (FD) has emerged as one of the most extensively studied research topics that spans multiple disciplines such as pattern recognition, signal processing and computer vision. This is due to its numerous important applications in identity authentication, security access control, intelligent human-computer interaction, and automatic indexing of image and video databases. Many approaches to face recognitions have been developed; an excellent survey paper on the different face recognition techniques can be found in [1].

The success of any FR methodology depends heavily on the particular choice of the features used by the (pattern) classifier. It is known that a good feature extractor for a face recognition system is claimed to select as more as possible the best discriminant features which are not sensitive to arbitrary environmental variations such as variations in pose, scale, illumination, and facial expressions. Feature extraction algorithms mainly fall into two categories: geometrical features extraction and, statistical (algebraic) features extraction [2 -8]. The geometrical approach , represent the face in terms of structural measurements and distinctive facial features that include distances and angles between the most characteristic face components such as eyes, nose, mouth or facial templates such as nose length and width, mouth position, and chin type. These features are used to recognize an unknown face by matching it to the nearest neighbor in the stored database. Statistical features extraction is usually driven by algebraic methods such as principal component analysis (PCA), and independent component analysis (ICA) [6]. These methods find a mapping between the original feature spaces to a lower dimensional feature space.

Face verification across age has been subject to relatively little attention. Some previous work applies age progression for face verification tasks. When comparing two photos, these methods either transform one photo to have the same age as the other, or transform both to reduce the aging effects. One of the earliest works appears in Lanitis et al. [18], where a statistical model is used to capture the variation of facial shapes over age progression. The model is then used for age estimation and face verification. Ramanathan and Chellappa [31] use a face growing model for face verification tasks for people under the age of eighteen. This assumption limits the application of these methods, since ages are often not available. A recent work in Biswas et al. [4] studies feature drifting on face images atdifferent ages and applies it to face verification tasks.

PROBLEM DEFINITION

Face detection can be regarded as a specific case of object-class detection. In object-lass detection, the task is to find the locations and sizes of all objects in an image that belong to a given class. Examples include upper torsos, pedestrians, and cars.

Face-detection algorithms focus on the detection of frontal human faces. It is analogous to image detection in which the image of a person is matched bit by bit. Image matches with the image stores in database. Any facial feature changes in the database will invalidate the matching process.

In this paper a new method has been proponed to select templates based on the PSO algorithm. Previous template based methods use face features such as eyebrows, nose and mouse as key features in the template. We call these templates anthropometric templates.This method was applied to the frontal face detection problem.

METHODOLOGY

A. Particle Swarm Optimization (PSO)

The PSO algorithm is a relatively new combinatorial heuristic algorithm based on the interaction of social systems such as fish schooling or bird flocking. Since the introduction of the PSO algorithm [4], several improvements have been proposed introducing new parameters for intensive search as well as to avoid solutions combinatorial explosion [1], [1 1]. The PSO algorithm simulates the individual’s social behavior (particles) moving in a multidimensional space. Each solution is identified with an individual particle which has specific coordinates in the search space. The particle position indicates the possible solution in the multidimensional space and the speed indicates the amount of change between the actual position and the next.

The algorithm stores the previous best position of each particle (Pi) [4]. This information is used in the adaptation of the position in the solution space between subsequent iterations. At initialization the algorithm generates a random particle population. Each particle is initialized with random position and speed. This initialization is performed within the established boundaries for each problem. AN important parameter is the particle maximum speed (Vmax). The particles speed is initialized in the range [-vmax,.-Vmax] [4]. After the initial population has been generated, a fitness function is evaluated. This evaluation is performed for each particle position storing this value. The actual result of the fitness function is compared to the best previous result for each particle.

B. PSO Templates

The method to generate templates using the PSO algorithm considers a set of templates for different face sizes. Figure 1 shows a block diagram of the template selection by PSO algorithm. The method is applied to frontal faces. The first step is to preprocess the input image by manually detecting the frontal face by determining the parameters. The face position and size is determined vertically by [y -Ayl,.y2 + Ay2] and horizontally by [xl,...,x2]. The segmented faces are converted to gray scale and normalized in size. The directional image contains the average of the tangent vectors in a 7x7 window in the normalized gray scale segmented image. The resulting set of directional images is used by the PSO algorithm.

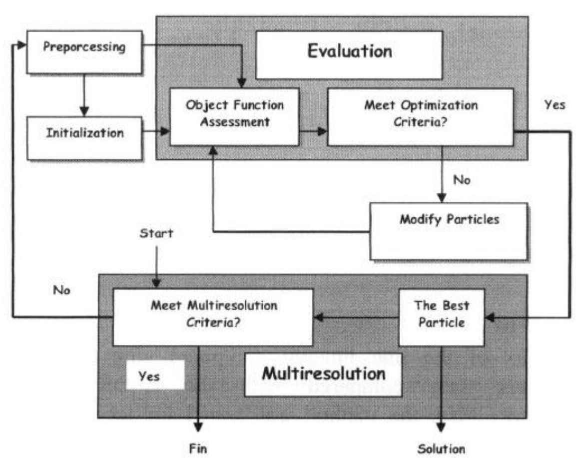

Fig. 1: Block diagram for the PSO template selection method.

IMPLICATIONS

Face detection plays an important role in a wide range of applications, such as mug-shot database matching, credit card verification, security system, and scene surveillance. Face detection is a challenging research topic since, even for the same person, faces appear differently due to lighting conditions, expression, pose, occlusion, and other confounding factors in real life [1]–[3]. The most popular existing technologies include eigenface [4], fisherface [5], independent component analysis [6], Bayesian face recognition [7], [8], active shape model [9], active appearance model [10], local feature analysis [11], and elastic bunch graph matching [12]. Due to the difficulties in controlling the lighting conditions in practical applications, the resulting variability in image illumination is one of the most challenging problems in face detection. The performance of the aforementioned techniques is heavily subject to the variations in the lighting conditions. Over the last decade, some approaches have emerged to attempt to tackle the problem of face recognition under varying illuminations.

LIMITATIONS

1. Image quality

Image quality affects how well facial-recognition algorithms work. The image quality of scanning video is quite low compared with that of a digital camera. Even high-definition video is, at best, 1080p (progressive scan); usually, it is 720p. These values are equivalent to about 2MP and 0.9MP, respectively, while an inexpensive digital camera attains 15MP. The difference is quite noticeable.

2. Image size

When a face-detection algorithm finds a face in an image or in a still from a video capture, the relative size of that face compared with the enrolled image size affects how well the face will be recognized. An already small image size, coupled with a target distant from the camera, means that the detected face is only 100 to 200 pixels on a side. Further, having to scan an image for varying face sizes is a processor-intensive activity. Most algorithms allow specification of a face-size range to help eliminate false positives on detection and speed up image processing.

3. Face angle

The relative angle of the target's face influences the recognition score profoundly. When a face is enrolled in the recognition software, usually multiple angles are used (profile, frontal and 45-degree are common). Anything less than a frontal view affects the algorithm's capability to generate a template for the face. The more direct the image (both enrolled and probe image) and the higher its resolution, the higher the score of any resulting matches.

4. Processing and storage

Even though high-definition video is quite low in resolution when compared with digital camera images, it still occupies significant amounts of disk space. Processing every frame of video is an enormous undertaking, so usually only a fraction (10 percent to 25 percent) is actually run through a recognition system. To minimize total processing time, agencies can use clusters of computers. However, adding computers involves considerable data transfer over a network, which can be bound by input-output restrictions, further limiting processing speed.

Ironically, humans are vastly superior to technology when it comes to facial recognition. But humans can only look for a few individuals at a time when watching a source video. A computer can compare many individuals against a database of thousands.

As technology improves, higher-definition cameras will become available. Computer networks will be able to move more data, and processors will work faster. Facial-recognition algorithms will be better able to pick out faces from an image and recognize them in a database of enrolled individuals. The simple mechanisms that defeat today's algorithms, such as obscuring parts of the face with sunglasses and masks or changing one's hairstyle, will be easily overcome.

An immediate way to overcome many of these limitations is to change how images are captured. Using checkpoints, for example, requires subjects to line up and funnel through a single point. Cameras can then focus on each person closely, yielding far more useful frontal, higher-resolution probe images. However, wide-scale implementation increases the number of cameras required

CONCLUSION

In this paper a new method has been proponed to select templates based on the PSO algorithm. Previous template based methods use face features such as eyebrows, nose and mouse as key features in the template. We call these templates anthropometric templates. It is argued that the new method has advantages relative to anthropometric templates because it looks for a template that maximizes the response of the line integral performed with the template over the face directional image. The method was applied to the frontal face detection problem. The method was applied to 2 video-sequences containing 466 and 202 frames respectively. Results show that the line integral values are larger for the PSO templates and also face size estimation is better with the PSO templates. The method also allows to control the maximum number of points in the template reducing the processing time.

FUTURE SCOPE

Face detection systems used today work very well under constrained conditions, although all systems work much better with frontal mug-shot images and constant lighting. All current face recognition algorithms fail under the vastly varying conditions under which humans need to and are able to identify other people. Next generation person recognition systems will need to recognize people in real-time and in much less constrained situations.

We believe that identification systems that are robust in natural environments, in the presence of noise and illumination changes, cannot rely on a single modality, so that fusion with other modalities is essential (see Figure 5). Technology used in smart environments has to be unobtrusive and allow users to act freely. Wearable systems in particular require their sensing technology to be small, low powered and easily integrable with the user's clothing. Considering all the requirements, identification systems that use face recognition and speaker identification seem to us to have the most potential for wide-spread application.

Cameras and microphones today are very small, light-weight and have been successfully integrated with wearable systems. Audio and video based recognition systems have the critical advantage that they use the modalities humans use for recognition. Finally, researchers are beginning to demonstrate that unobtrusive audio-and-video based person identification systems can achieve high recognition rates without requiring the user to be in highly controlled environments.

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