An Improved ABC Algorithm Approach Using SURF for Face Identification

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Abstract. Face recognition is being intensively studied in the areas of computer vision and pattern recognition. Working on still images with multiple faces is a challenging task due to the inherent characteristics of the images, the presence of blur, noise and occlusion, as well as variations of illumination, pose, rotation and scale. Besides being invariant to these factors, face recognition systems must be computationally efficient and robust. Swarm intelligence algorithms can be used for object recognition tasks. Based on this context, we propose a new approach using an improved ABC implementation and the interest point detector and descriptor SURF. To assess the robustness of our approach, we carry out experiments on images of several classes subject to different acquisition conditions.

Keywords: Face Identification, Image Variations, Interest Point Detectors, Swarm Intelligence, ABC algorithm, SURF, Still Images.

1 Introduction

Face recognition systems are generally classified into two categories: face verification and face identification. The first performs the matching between a query face image and a template, and the second compares the query image against several templates of a database [1]. In other words, the identification requires a onetomany matching process, while the verification is performed considering a onetoone image matching. In real world applications, the input images may be subject to different degradation problems during the acquisition procedure. These problems may occur due to several reasons, including environmental conditions (non-uniform illumination, occlusion and changes in pose and scale) and intrinsic face image characteristics (expression, hair styles, cosmetics and aging). Over the last two decades, several works have been proposed to make face recognition systems less sensitive to some of these problems, but only a few consider still images with multiple faces, focus of this work.

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Still images with multiple faces may have complex background and comprise two main issues on a face identification process: the searching and detection of each face under different image conditions and the matching of a face object image against the faces obtained from still images. Real-life face recognition applications typically require accurate and fast search algorithms and matching methods at all stages [2]. According to Chellappa [3] in geometrical features based systems, window-based local processing to locate feature points using iterative search algorithms can be applied. Hence, the searching process in still images can be done using swarm intelligence optimization algorithms, such as Particle Swarm Optimization (PSO) [4] or ABC (Artificial Bee Colony) [5], for example. These approaches are computationally inexpensive, decentralized, adaptive and are not based on an explicit model of the environment [6]. Metaheuristic population-based optimization algorithms, such as those above mentioned were successfully applied in the development of fast algorithms for recognition problems [7] and are the basis of the approach proposed in this paper.

To reduce the associated computational cost of the second issue, instead of matching all image pixels (as in the traditional template matching approach), an alternative could be to match some features extracted from invariant image locations [8]. In this context, interest points can be considered to describe image features like color, texture and shape. Since its development, interest points have been mainly applied for object recognition and other related tasks [9].

The main objective of this work is to present a novel approach using the improved ABC algorithm (iABC) [7] to search and identify faces in still images, based on features generated by the interest point detector and descriptor, SURF (Speeded-UP Robust Features). Although there are many other ways to search and recognize faces in still images using SURF, the computational experiments carried out in this work show that its combination with a swarm intelligence approach yields accurate and efficient results during an iterative search and matching process. Since the focus of the present work is to identify faces in still images using iABC with SURF, we have also formulated this problem as an optimization problem where optimal values for image parameters have to be determined. To evaluate the proposed approach we conduct several computational experiments with real digital images acquired under different image conditions. This is the main contribution of the present work.

This paper is organized as follows. In Section 2, related topics and works regarding interest point detectors, SURF and ABC algorithm are explained. Experimental details and results are discussed in Section 3. Finally, Section 4 outlines some conclusions and future work.

2 Related Topics and Works

2.1 ABC Algorithm for Face Identification

In the ABC algorithm [5], each food source is considered as a possible solution for an optimization problem. The amount of employed bees represents the number of solutions (SN) in the population. Each solution is represented by

X_i, $i \in (1, ..SN)$, a d-dimensional vector where d corresponds to the number of parameters to be optimized. Once the employed bees are created, the search process starts and it is repeated by a predefined number of cycles, defined by the Maximum Cycle Number (*MCN*) value. Thus, the basic ABC algorithm has three control parameters determined at the beginning of the search process: *SN*, *Limit* and *MCN*. The parameter *Limit* is the product of dimension (d) by the number of initial solutions (*SN*).

For the face identification problem using ABC algorithm, a face image is represented by a 4-tuple, denoted by (x, y, s, θ), representing the coordinate values of column and row of the central point, scale and rotation, respectively. Such transformation parameters are optimized to determine the most similar face in a still image. In our image context, the search space is limited by restricting the range of each parameter as follows: $0 \leq x \leq n$, $0 \leq y \leq m$, $0.5 \leq s \leq 1.5$ and $-\pi/2 \leq \theta \leq \pi/2$. A bee (or solution) corresponds to a position in the still image, represented by a 4D vector $X_{id}(X_{i1}, X_{i2}, X_{i3}, X_{i4})$, where $d = 4$ and $i \in 1, ..SN$.

The following pseudocode summarizes briefly the basic ABC algorithm [5] used for the definition of improved iABC:

1. Initialize the population of employed bees (positions) of size SN;
2. Evaluate the fitness of initial population;
3. Repeat until the stopping criteria is met(cycle = MCN):
   (a) *Produce new neighborhood solution (positions) and evaluate their fitness;*
   (b) *Move the employed bees to new solutions (positions);*
   (c) *Calculate the probability values for the solutions;*
   (d) *Produce the new solutions for the onlookers using the probability values and compute their fitness;*
   (e) *Move the onlooker bees to new solutions (positions);*
   (f) *Produce scout bees;*
   (g) *Increment cycle;*

As shown in the pseudocode, during the steps 3(a) and 3(d), employed and onlooker bees perform the local search process to find out the optimal solutions, meanwhile, in step 3(f), by evaluating the Limit value, scout bees are produced to perform global search, aiming at finding new unexplored solutions. The basic ABC algorithm perturbates only one parameter at time when a new neighborhood solution is generated for both employed and onlooker bees, during the steps 3(a) and 3(d). At the end of step 3(f), if possible, when the limit counter value of a specific solution exceeds the *Limit*, one scout will be generated even though it can be more than 5% of the population [10]. If none of the solution exceeds the *Limit* value, no scout bee will be produced. Based on this context, three different mechanisms for improving the ABC were studied, such as the generation of scout bees, perturbation of all variables and explosion of stagnated population.

To define the iABC version, the basic ABC algorithm [5] was tested with the combination of three improvement strategies. According to the iABC, for the object recognition problem using landscape images, the generation of randomly created scout bees produced no significant effect in performance, even though scout bees mechanism can improve the global search ability of the ABC algorithm. On the other hand, the use of explosion of stagnated population mechanism was shown to accelerate the convergence of the algorithm without losing quality of solutions. Based on the experimental analysis, the iABC was defined by selecting the best strategy which consists of perturbation of multiple variables, explosion and without generation of scout bees. Overall, the improved ABC, proposed by Chidambaram and Lopes [7], can be a good alternative to real-world object identification problems. Hence, in this work, we use the iABC algorithm, to search and identify faces in still images.

2.2 Interest Point Detectors

An interest point detector is an algorithm that uses an image as input and outputs a set of points that can be identified with high repeatability in location. Interest points can be defined as a set of image pixels that have high level of variation in reference to a predetermined local measure [11]. Compared to low-level features like color, interest points are considered more stable and reliable [12]. Most of the detectors finally generate descriptor vectors which contain the information regarding the neighborhood of every interesting point in an image. Object recognition can be considered as one of the main application of interest point detectors [9]. Among many detectors and descriptors, two of them can be mentioned as most known recently: Scale Invariant Features Transform (SIFT) [9] and Speeded-Up Robust Features (SURF) [8].

In 2008, Bay and colleagues [8] developed a novel scale and rotation-invariant detector and descriptor, called SURF. Although SURF can be conceptually similar to SIFT, SURF is less sensitive to noise, invariant to scale and rotation and outperforms SIFT. SURF builds a descriptor vector of 64 dimension using relevant feature information arround every interest point. SURF descriptors reduce the time for feature computation and matching, and also increases robustness. Repeatability rate is the only measure of stability which is strongly accepted as a standard computer vision performance metric for interest points [11]. Measurements of repeatability will quantify the number of repeated points detected under varying conditions, i.e, the percentage of matched points that are repeated in both images.

3 Computational Experiments and Results

The search and identification using iABC with SURF for finding image correspondences is repeated as an iterative optimization process. This process is similar to the template matching in which maximum correlation (the best possible match) is possible when the incoming object image is identical to the imaget cut from the still image. According to the nature of this work, face detection is not done explicitly rather it is indirectly associated with the identification step. As the initial step, the interest points of the still image and face object image are calculated using SURF. In the next step, interest points of still image, mainly descriptors of 64-D vector, are stored in a separate matrix structure (the same size of still image) at the corresponding keypoints (coordinates) of interest points. This matrix structure is created to avoid the calculation of interest points for each image cut from the still image during the iterative process. Using a 4-D vector for each individual of the population, a face image is obtained from the still image and its interest points (descriptors) are obtained from the corresponding coordinates in the matrix. Thus, this procedure can reduce the computational effort that will be spent on interest points calculation. It is important to mention that each cut of image from still image could possibly be an optimal solution or the exact face image that has to be identified. During the matching stage, the interest points correspondences between images are identified using distance measures of keypoints or coordinates and descriptors.

The iABC algorithm was implemented C programming language with OpenCV functions. All experiments were run on a cluster of computers using Pentium quad-core processors under Linux. For our tests, we have defined the number of employed bees (or initial solutions) SN = 80, MCN = 100 and *Limit* was not used, as defined in Section 2.1. The number of runs was set to 30. During the search, when stagnation occurred for 30% of the MCN, explosion was performed. In addition to these ABC parameters, to evaluate the matching of interest points, two more control parameters were used to determine the matching points between the face object image and the face obtained from the still image using descriptors and coordinates: (1) keypoints or coordinates distance threshold (set to 50); (2) descriptor distance threshold (set to 0.09). Both values were determined empirically. The fitness was calculated using the number of matched interest points against the number of interest points of face object image.

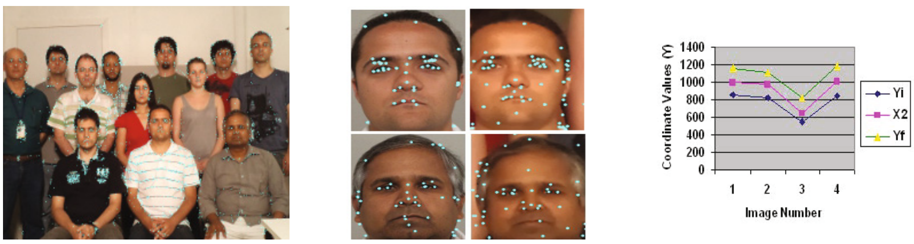
We have performed nine experiments to show the robustness of the proposed approach. These experiments widely cover the different image conditions that occur in real-world. The most relevant results are discussed in this section. All face object images that were used in the experiments were obtained separately and are different from those in the still images. Images were captured under two different illumination conditions: (1) Under controlled illumination condition using a specfic lighting system; (2) uncontrolled illumination condition. Under uncontrolled illumination, the image aquisition was done in two ways: under natural lighting conditions (flourescent lights) of the room, and also, with partially controlled illumination. The latter is used only for still images. All face object images used in this work were obtained under controlled illumination.

The first experiment was done using a still image obtained under controlled condition and without any variation. In Table 1, some result data are shown such as central coordinate values of the identified face in still image (X_1 and X_2), average fitness of best solutions, number of times the face was correctly found in still image within 30 runs (Num. Id), the left-top corner (X_i and Y_i) and the right-bottom corner (X_f and Y_f) coordinate values of face in still image, and the average number of evaluations per run (Num. Eval). The execution time and the number of evaluations are included in this work for comparison purposes of performance with other approaches.

Table 1. Solutions found by iABC using still image without any variation obtained under controlled condition

	Coordinates of face found by iABC					Num.	Coordinates of face in still image				Exec.	Num.
Image	X_1	X_2	*Angle*	*Scale*	*Fitness*	*Id*	X_i	Y_i	X_f	Y_f	*Time*	*Eval*
1	2102	1003	−0.008	0.946	0.3196	29	1980	860	2250	1170	861	25348
2	1446	971	−0.013	0.999	0.4667	30	1310	820	1540	1120	837	31240
3	1287	650	−0.064	0.898	0.2474	29	1164	560	1354	820	1028	25511
4	751	1013	−0.173	0.915	0.3222	29	640	850	880	1190	1058	34022

From the results of the first experiment shown in Table 1, it can be observed that the angle values are relatively close to zero, since the faces in still image are almost without any rotation. The scale values varies from 0.9 to 0.99 which indicates that the face obtained from still image is almost of the same size of face object image presented to the algorithm. In the same table, the fitness values vary from 0.24 to 0.47 and represents the matched interest points of face region from still image and face object image. In addition to these data, the images with interest points are shown in the Figure 1 (a) and (b). The main goal of this work is to locate and identify the face object image within the region of face in still image. Hence, no exact match of coordinates is expected. This can be observed from X_1 and X_2 whose values are within the range of X_i and Y_i, and X_f and Y_f. It is demonstrated in Figure 1(c) by the y coordinate value (X_2- middle line) of the identified face image by iABC. To determine the identification rate of face image, this condition was observed in all other experiments.



(a) (b) (c)

Fig. 1. Images with interest points - Still image (a), Face object images (1st Column) and Faces from still image (2nd Column) (b), Coordinate value Y (X_2) of identified face by iABC within the region of face in the still image (between Y_i and Y_f)) (c)

To test the robustness of the iABC algorithm with SURF, we have also conducted experiments using images obtained under different conditions and artificially manipulated images as shown in Table 2. The identification rate is the ratio of the number of times the face object image was identified by the number of runs in each experiment. For example, in the first experiment, even though the still image is obtained under controlled condition, the average identification rate is about 88% among eight experiments. This is because of one face object image which has significant variation in comparison with the face in still image. In the next two experiments, using the same face object images as in the first experiment and still images obtained under partially controlled and uncontrolled illumination, the average identification rate reached 72% and 13%, respectively. Such results confirm the well-known influence of illumination conditions in the recognition process.

Table 2. Result data of all experiments

Experiment Description (Image Type)	Num. of Images	Num. of Experiments	Average ID. Rate
Controlled Illumination	08	08	88%
Uncontrolled Illumination	08	08	13%
Partially Controlled Illumination	08	08	72%
Face Images with occlusion	04	04	54%
Rotation (-30 to +30 degrees)[1]	02	20	100%
Scale Variation (80% to 120%)[1]	02	16	97%
Gaussian Blur (04 levels)[1]	02	08	33%
RGB Noise (04 levels)[1]	04	16	100%
Illumination Variation (04 levels)[1]	04	16	99%

[1]Artificially Manipulated Images

The identification rate in the experiment with occluded faces reached about about 54%. This type of images may require more investigation using different levels of occlusion. However, in our study, the results show that the proposed approach is capable of identifying faces in such conditions. All other experiments were conducted using artificially manipulated images. The SURF is considered invariant to scale and rotation and is also less sensitive to noise [8]. Based on this point, the still image variations are divided into the following categories: RGB noise, Gaussian blur, changes in lighting, rotation and scaling. Increasing levels of Gaussian blur and RGB noise were added to the still image. Rotated images were generated in both clockwise and counterclockwise directions, varying from -30 to +30 degrees in increments of 5 degrees. Likewise, scaled still images were obtained by varying its original size from 80% to 120% in increments of 5%. Among these categories, only in Gaussian blurred images, the identification rate is about 33%, meanwhile, in the other categories, the iABC algorithm was robust enough to identify the face images in almost all experiments.

4 Conclusions

In this work, a new approach using iABC with the interest point detector SURF is proposed for the face identification problem. The promising results obtained from some relevant experiments showed that the proposed iABC with SURF can effectively work with images under different conditions and it can be suitable for face identification and related tasks. Thus, the proposed approach is robust to work with still images with mutiple faces. This approach differs from other similar works in the literature by the way the face identification process is conducted with aid of iABC algorithm. Besides this point, face detection is not done explicitly and it is indirectly associated with the face identification process which is driven by the evolution of the population using the interest points matching function. According to the experimental results, it can be observed that the illumination variation influences the face identification process. Consequently, this issue requires more research effort and deep study. In addition to this, future work will focus on reducing the number of evaluations and, consequently, the execution time.

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