Pattern Recognition 74 (2018) 385–405

Contents lists available at ScienceDirect

Pattern Recognition

journal homepage: www.elsevier.com/locate/patcog

A multi-objective optimization model and its evolution-based solutions for the fingertip localization problem

Dunwei Gong [a,b], Ke Liu [a,*]

[a] School of Information and Control Engineering, China University of Mining and Technology, Xuzhou 221116, China
[b] School of Information Science and Technology, Qingdao University of Science and Technology, Qingdao 266061, China

ARTICLE INFO

Article history:
Received 6 January 2017
Revised 31 August 2017
Accepted 2 September 2017
Available online 14 September 2017

Keywords:
Fingertip localization
Multi-objective optimization
Estimation of distribution algorithm
Probability distribution model

ABSTRACT

Exact fingertip positions are of particular importance to the fingertip-based human–computer interaction. We build a multi-objective optimization model for the problem of fingertip localization, and present a method to solve the above model based on evolutionary algorithms. When building the model, we take the positions of a series of pixels as the decision variable, the shape of the hand-edge curve corresponding to each of the pixels as one objective function, and the distance between each of the pixels and the gravity center of the palm as the other objective function. In addition, based on the correlation among the positions of pixels of the fingertip regions, we present a multi-objective estimation of distribution algorithm to solve the model so as to obtain the best pixel set, thus gaining the fingertip positions. The experimental results demonstrate the effectiveness of the proposed model and algorithm.

1. Introduction

Human–computer interaction is an important way to accomplish complex tasks. During the human–computer interaction, making a computer understand the behavior of a human is of considerable importance. Among various behaviors, one based on a human's fingertips can express rich information. Therefore, exactly locating a human's fingertips is very important to the cooperation of a human and a computer to accomplish a given task.

We can gain a binary image of a hand by gesture segmentation [1,2]. Following this, fingertip localization is adopted to obtain the coordinates of each fingertip in the image. There have been several categories of methods in solving the problem, such as the fingertip localization based on contour curvatures [3–5] and the fingertip localization based on a hand skeleton [6,7], among many others. However, these methods generally have a low accuracy of locating fingertips, due to lack of the mechanism with which a human processes visual signals. The so-called accurate localization of fingertips is to obtain the coordinates of the center of each fingertip region.

A fingertip is the upper part of a finger, and covered by a fingernail. Compared with the other parts of a hand, each fingertip has a prominent position, and is easy to be identified by the shape of its edge, which can be called as the two features of each fingertip region. If we select a number of pixels whose features are closest to the two features of fingertip regions from all the hand pixels, the coordinates of the center of each fingertip region can be calculated based on these selected pixels. Based on the above analysis, the problem of selecting the pixels of fingertip regions is essentially an optimization problem.

The distribution of each fingertip center has certain randomness in a hand region. But the edge of the fingertip region is approximately a semicircle arc, and the fingertip region is prominent. So we can formulate fingertip localization as a multi-objective optimization problem to select fingertip pixels according to the above two features of each fingertip region. Fingertip localization is to obtain the position of each fingertip center from a hand region. The fingertip center is in the fingertip region, so it is not accurate to obtain the fingertip center from the hand edge. If we formulate fingertip localization as a multi-objective optimization problem, we can obtain the fingertip center whose position may be in the fingertip region and similar to its real position.

In this paper, a multi-objective optimization model for fingertip localization is built, and a method of solving the above model is presented. When building the model, we take the positions of a series of pixels as the decision variable, the shape of the hand-edge curve corresponding to each of the pixels as one objective function, and the distance between each of the pixels and the gravity center of the palm as the other objective function. In addition, based on the correlation among the positions of pixels of the fingertip regions, we present a multi-objective estimation of distribution algorithm (EDA) to solve the model so as to obtain the best pixel set,

* Corresponding author.
E-mail addresses: dwgong@vip.163.com (D. Gong), liu791018@126.com (K. Liu).

http://dx.doi.org/10.1016/j.patcog.2017.09.001
0031-3203/

thus obtaining the fingertip positions. In this EDA, the probability distribution model and the sampling method are both aimed at the multi-objective optimization model for fingertip localization.

The main contributions of this paper are mainly reflected in the following three aspects: (1) A multi-objective optimization model for the problem of fingertip localization is built. (2) A multi-objective EDA based on the correlation among the positions of pixels of the fingertip regions is proposed, including a suitable probability distribution model and a new sampling method. (3) The effectiveness of the proposed model and algorithm is verified by a series of experiments. The work of this paper provides a feasible and efficient way to solve the fingertip localization problem.

The remainder of this paper is arranged as follows. Section 2 reviews related work. A multi-objective optimization model for fingertip localization is built in Section 3. Section 4 proposes a multi-objective EDA based on the correlation among the positions of pixels of the fingertip regions. The applications of the proposed model and algorithm in actual problems of fingertip localization are provided in Section 5. Finally, Section 6 concludes this paper, and points out topics to be further studied.

2. Related work

In this paper, we study the problem of fingertip localization. After building a multi-objective optimization model for the above problem, we adopt a multi-objective evolutionary optimization method to solve the above model. In the following, we will give a detailed review of related research.

2.1. Fingertip localization

After segmenting a hand region, a system of human–computer interaction based on the positions of fingertips can find the coordinates of each fingertip. During processing a gesture image, the localization of fingertips is usually based on their shape. In [8], a hand model is utilized to locate fingertips, which is represented by a probability density function. This probability density function considers the location parameters, i.e., rotational angle and translation vector. So the probability that an observed feature configuration corresponds to the trained feature configuration can be obtained. In [9], an input image splits into R, G, and B planes. Edges are detected in each plane by Canny edge detection with initial Canny edge thresholds, and then detected edge regions are expanded in each plane by morphological gradient and smoothing. The pixel values of edge regions in each plane are compared, and the pixels which have the maximum pixel value among the three planes are selected as an edge. Then, the number of edge pixels is compared with the pixel number threshold to find a fingertip edge.

In recent years, a number of methods have been developed for fingertip localization. In [10], Wu et al. proposed an algorithm for finding the local maximum distance outside circles of extended centroid distance for fingertip localization. In the case of the circle whose radius is the average centroid distance, it is easy to determine the number of pixels on the circle. When calculating a great number of consecutive pixels, they can be sure that this region is a wrist and therefore remove the corresponding contour points. Because the circle is rotationally invariant, even if the hand rotates, the algorithm still works. In [11], Suau et al. addressed the problem of fingertip location by making use of the oriented radial distribution descriptor in a structured inference framework. Maxima of the oriented radial distribution of the input patch are likely to represent fingertip positions. In [12], Prasertsakul et al. presented a fingertip detection method that is based on the top-hat transform. The palm of the hand is obtained using the morphological opening. Fingertips are then obtained as the opening residue, the difference between the input image and the palm image. In [13], Wang et al. extracted the gesture contour, calculated gesture gravity and used the Douglas–Peucker algorithm to approximate contour polygons. Then they detected the convexity defects of the approximated contour as the fingertip points of the candidate.

Additionally, Candela et al. [14] combined the method based on the curvatures of a hand contour with the method based on the skeleton of a hand, and located fingertips through the following two phases. They firstly seek the candidate positions based on the curvatures of a hand contour, and then obtain the accurate positions of fingertips from these candidate positions based on the skeleton of the hand. With the trained classifier, Jang et al. [15] initially detected the candidate points of the fingertips by selecting the maximum probability between true and false choices. Then they found the center position of each fingertip from clustering the candidate points into five groups of points. Heo et al. [16] located fingertip based on the relationship of position between fingertip and center of palm. The finger range is decided between the palm and hand range which are calculated through the analysis of the areas ratio to the polar transform image. The fingertips are detected by k-curvature method which is defined by tangential differentiation of a curve function within the finger range. The use of the curvature method for the detection of fingertips can easily lead to erroneous results, due to interference from false inflection points. Thus, Ho et al. [17] proposed a method for the selection of candidate points with less interference. The point with the greatest curvature among the candidate points is identified as the fingertip. The contours of the finger obtained via edge detection is first presented in the form of an universal set. The contour of the finger poses a problem in that the contour cannot be as loses smoothness due to digitization errors; there are, such that a number of inflection points may be misinterpreted as fingertips. The proposed candidate points method eliminates points that could cause interference, thereby ensuring that the points with the greatest curvatures are indeed the fingertips.

2.2. Multi-objective evolutionary optimization

In real-world applications, one often encounters problems with simultaneously optimizing multiple objectives under specific conditions. They are so-called multi-objective optimization problems. For a multi-objective optimization problem, its objectives often conflict with each other. That is, the improvement of one objective is at the cost of deteriorating one or more other objectives. Therefore, one can obtain a solution set that compromises all the objectives of the optimization problem. To tackle multi-objective optimization problems, scholars have combined evolutionary algorithms [18,19] with multi-objective optimization, developed a variety of methods, and formed a popular research topic, i.e., multi-objective evolutionary optimization [20,21].

Schaffer [22] proposed that evolutionary optimization methods can be employed to solve multi-objective optimization problems, which is the pioneering work of solving multi-objective optimization problems by using evolutionary algorithms. Later, Srinivas and Deb proposed non-dominated sorting genetic algorithm (NSGA) [23] for solving multi-objective optimization problems. Deb et al. improved NSGA, and proposed a famous algorithm, NSGA-II [24]. Since then, a variety of efficient multi-objective evolutionary algorithms have been proposed based on NSGA-II [25–27]. Additionally, scholars have proposed many other multi-objective evolutionary optimization algorithms [28,29].

Compared with genetic algorithms based on the micro mode in the search space [30–32], Estimation of distribution algorithm is based on the macro counterpart in the search space, and has a stronger capability in exploration and a more rapid convergence speed [33,34]. Zhang et al. proposed regularity model-based multi-objective estimation of distribution algorithm (RM-MEDA) [35],