Edge Extraction for Human Body Images based on ACAFCM Algorithm

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Abstract—**Image edge extraction is an important process in obtaining anthropometric information from human body images captured by ordinary cameras. Depending on the characteristics of the large pixel matrix and the fuzzy edge of the image, the ant colony and fuzzy C-means clustering (ACAFCM) algorithm is used to get a clear and complete edge contour of the human body. This Canny algorithm is used to preprocess image segmentation, binarization, and de-noising by simplifying the image color and noise. The ant colony algorithm determines the initial center and number of clusters, and it distinguishes the pixels, based on the target, background, edge, and noise of the pretreated image. The FCM algorithm clusters the pixels with the same attributes into one class, and it extracts a clear and complete edge contour of the body image.**

Index Terms—**photography; human body image; edge extraction; ACAFCM algorithm**

I. Introduction

Photography can be used as a method for 2D non-contact anthropometric measurement [1]. Images of the human body are captured by a camera, usually from the front and side views, and the body dimensions are obtained from the images by applying image processing techniques. The advantages of this method are low cost and convenience. Performing edge extraction on the body image is the key step in discerning the target from the background [2][3]. Many research studies focused on finding and using a different algorithm to achieve a more accurate and more effective method to perform edge extraction. In this study, the ACAFCM algorithm is used.

II. ACAFCM Algorithm

This section introduces the combination of the ant colony algorithm (ACA) and the fuzzy C-means (FCM) clustering method used in image edge extraction. The processing steps and the advantages of the combined algorithms are discussed in detail.

A. ACA Algorithm

The ACA algorithm is a novel simulated evolution algorithm [4-8]. It realistically simulates the foraging behavior of an ant colony in the natural world.

The schematic diagram of a foraging ant colony is shown in figure 1. The point “O” represents the ant nest, which is the starting point of ant foraging. The point “F” represents the food source, and the line “DB” represents the obstacles. Suppose that only two paths exist around obstacles to reach the food source: Path “a” and Path “b.” Path “a” is shorter in distance than Path “b.” Usually, the shortest path is chosen as the best foraging path from the nest to the food source.

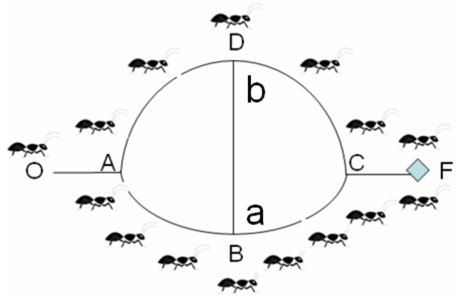

Figure 1. Ant colony foraging principle diagram

B. ACA Algorithm for Image Edge Extraction [5]

When using the ACA algorithm [9], edge extraction can be viewed as the process of classifying pixels with different attributes. The initial cluster center is set according to the pixel characteristics (i.e., target, background, edge, and noise) of the image. Here the clustering behavior of ant colony foraging is used to explain the problem of image edge extraction.

Problem space

The three-dimensional space of the ant colony foraging clustering problem is interpreted as the two-dimensional space of the image edge extraction.

Individual transformation

Each ant is equivalent to a pixel in the image.

Search path

The ant colony foraging path is defined as the track formed by clustering according to different attributes of pixels, resulting in the extraction of the image edge.

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Pheromone releasing

The ant behavior of releasing pheromones in the foraging path is equated to the probability of pixel clustering based on a certain attribute.

Expected results

The process of searching for different food sources is equivalent to the process of image edge extraction.

To achieve image edge extraction, pixel clustering is based on three attributes: grayness, gradient, and neighborhood.

First, the value of each path pheromone concentration is set to zero; i.e., $\mu_{ij}(0) = 0$. The clustering radius is set to r, and the statistical error is set to ϕ. Euclidean distance is used to calculate the distance d_{ij} from pixel p_i to pixel p_j. The distance d_{ij} is represented as follows:

$$d_{ij} = \sqrt{\sum_{m=1}^{n} f_m (p_{im} - p_{jm})^2} \tag{1}$$

In equation 1, n is the dimension of the pixels where $n = 3$, and f is the weighting factor, which is based on the degree of impact of the three pixel components that influence clustering. The amount of pheromone concentration changes over time and is set as $\mu_{ij}(t)$, i.e.,

$$\mu_{ij}(t) = \begin{cases} 0 & d_{ij} > r \\ 1 & d_{ij} \le r \end{cases} \tag{2}$$

The probability R_{ij} of selecting a specific path from pixel p_i to pixel p_j is

$$R_{ij}(t) = \frac{\mu_{ij}^{\alpha}(t)\eta_{ij}^{\beta}(t)}{\sum_{x=1}^{j} \mu_{xj}^{\alpha}(t)\eta_{xj}^{\beta}(t)} \qquad j \in X \tag{3}$$

In equation 2, $\eta_{ij}(t)$ is the heuristic guide function. In the basic ACA, $\eta_{ij}(t) = 1/d_{ij}$. α is the pheromone that is accumulated in the pixel clustering process. β is the impact factor used by the heuristic guide function in choosing a path.

The data set of the selectable path is defined as

$$X = \{ p_x \mid d_{xj} \le r, x = 1, 2, ..., l \}$$

If $R_{ij}(t) > R_0$ and R_0 is a threshold value, then pixel p_i will be added to the area that includes pixel p_j. If the data set of pixel p_i to be merged with the neighborhood of pixel p_j is Y_j, then

$$Y_j = \{ P_q \mid d_{qj} \le r, q = 1, 2, ..., j \}$$

The clustering center is obtained as follows:

$$o_j = \frac{1}{j} \sum_{x=1}^{j} p_x, \quad p_x \in Y_j \tag{4}$$

The deviation error of the j clustering is as follows:

$$\mathrm{E}_{ij} = \sum_{x=1}^{j} (\sum_{i=1}^{2} (p_{xi} - o_{ji})^2)^{\frac{1}{2}} \tag{5}$$

In equation 5, o_{ji} is represented as the i component of the j cluster center, and the overall error is calculated as follows:

$$\phi = \sum_{j=1}^{x} \mathrm{E}_j \tag{6}$$

When $\phi \le \phi_0$, the program will output the number of clusters and the cluster centers.

In the clustering process for each path, the pheromone concentration changes through time. After the first cycle, the amount of pheromone concentration on each path is adjusted as follows:

$$\mu_{ij}(t) = \tau \mu_{ij}(t) + \Delta\mu_{ij}(t) \tag{7}$$

In equation 7, τ is the degree of pheromone attenuation through time, and $\Delta\mu_{ij}(t)$ is the increment value of the pheromone concentration on the path during this time cycle. This increment value is defined as follows:

$$\Delta\mu_{ij}(t) = \sum_{x=1}^{l} \Delta\mu_{ij}^{\ x}(t) \tag{8}$$

In equation 8, $\Delta\mu_{ij}^{\ x}(t)$ is the pheromone concentration that remains on the path with pixel x at time t.

C. FCM Algorithm

The FCM algorithm is an improvement on the ordinary C-means algorithm [10-15]. The FCM algorithm uses flexible fuzzy division. Its basic idea is that the similarity of the objects in the same class is maximized, and the similarity of objects in a different class is minimized.

D. Mathematical Model of FCM

a. FCM objective function

The general form of the FCM objective function is as follows:

$$J(U, c_1, ..., c_m) = \sum_{i=1}^{m} J_i = \sum_{i=1}^{m} \sum_{j}^{n} u_{ij}^{m} d_{ij}^{2} \tag{9}$$

In equation 9, $u_{ij} \in (0,1)$ and c_i is the cluster center of the fuzzy group i. d_{ij} is the distance between the i cluster center and the j data point, i.e., $d_{ij} = \| c_i - x_j \|$. m is the weighted index number, and $m > 1$.

We constructed a new objective function in order to minimize the above equation, as follows:

$$\overline{J}(U, c_1, ..., c_m, \lambda_1, ..., \lambda_n) = J(U, c_1, ..., c_m) + \sum_{j=1}^{n} \lambda_j (\sum_{i=1}^{m} u_{ij} - 1) = \sum_{i=1}^{m} \sum_{j}^{n} u_{ij} d_{ij}^2 + \sum_{j=1}^{n} \lambda_j (\sum_{i=1}^{m} u_{ij} - 1) \tag{10}$$

In equation 10, λ_j is the Lagrange multiplier, and $\lambda_j \in [1, n]$.

We calculated the derivatives of all the input parameters, which are necessary to minimize the equation, as follows:

$$c_i = \frac{\sum_{j=1}^{n} u_{ij}^m x_j}{\sum_{j=1}^{n} u_{ij}^m} \tag{11}$$

$$u_{ij} = \frac{1}{\sum_{l=1}^{n} \left(\frac{d_{ij}}{d_{lj}} \right)^{\frac{2}{m-1}}} \tag{12}$$

E. FCM Algorithm for Image Edge Extraction [7]

Due to the fuzziness and uncertainty of the image boundary, we applied the FCM algorithm [16-18] to our image edge extraction. With FCM, each pixel of the image is regarded as a data point of the sample, and each characteristic of the pixel is seen as a characteristic of the sample.

The specific steps of the FCM clustering algorithm are as follows:

a. Random number generation is used to produce the initial matrix of the membership $U^{(1)}$. The weighted index m and the number of clusters c are set. The threshold value that would end the iteration is $\varepsilon = 0.01$. The iteration counter is cleared.

b. The cluster center V is calculated as follows:

$$V_i = \frac{\sum_{l}^{n} (u_{il})^m x_l}{\sum_{l}^{n} (u_{il})^m}, \quad i = 1, 2, ..., c, \quad l = 1, 2, ..., n \tag{13}$$

c. The membership value u_{il} is set as follows:

$$u_{il} = \frac{1}{\sum_{j=1}^{c} \left(\frac{\|x_i - V_i\|}{\|x_i - V_j\|} \right)^{\frac{2}{m-1}}}, \quad i = 1, 2, ..., c, \quad l = 1, 2, ..., n \tag{14}$$

d. Steps “b” and “c” are repeated until the following equation is satisfied:

$$\left\| U^{(K)} - U^{(K-1)} \right\| < \varepsilon \tag{15}$$

F. ACAFCM Algorithm for Image Edge Extraction

The matrix of pixels in the image can be very large. If the ACA alone is used for image edge extraction, the computational amount becomes greater during the cyclic search, and the running speed becomes slower, which affects the convergence rate.

If the FCM algorithm alone is used for image edge extraction，the initial cluster center and the number of clusters tend to be random. Complex data have a strong sensitivity to the initial cluster center, making it easy to fall into the local optimum.

Therefore, in performing edge extraction on human body images, the ACAFCM algorithm combines the two algorithms to solve the problem better. Due to the large scale and uncertainty of the image pixels, the ACA obtains the initial cluster center and the number of clusters from the pixel data. Then these values are used as the initial parameters for the FCM algorithm to obtain the final classification information. Based on the classification information, the result of the image edge extraction is obtained.

The steps of the ACAFCM algorithm are described below, using the following initial set of parameters:

$$t, \alpha, \beta, r, \mu, R_{ij}$$

a) The distance d_{ij} from pixel p_i to pixel p_j is calculated according to equation 1.

b) The pheromone concentration $\mu_{ij}(t)$ on each path in the clustering process is calculated according to equation 7.

c) The probability R_{ij} of pixel p_i merging with the set that includes pixel p_j is calculated. If it is greater than a threshold value, p_i is merged with the set that includes pixel p_j.

d) The cluster centers are calculated according to equation 4.

e) The overall error is calculated according to equation 6. If it satisfies $\phi \le \phi_0$, then the cluster center and the number of clusters in the class are outputted.

f) The cluster center obtained by ACA is used as the initial cluster center for the FCM algorithm. Likewise, the number of clusters in the class obtained by ACA is used for the FCM algorithm.

g) The likelihood or degree of membership u_{il} of sample l in class i using the FCM algorithm is calculated according to equation 12.

h) The new cluster center V_i is calculated according to equation 13.

i) The degree of membership u_{il} is updated according to equation 14.

j) The distance errors ε of the new cluster center and the last cluster center are calculated. The iteration ends when the distance errors meet the condition in equation 15.

The human body image needs to be processed prior to extracting the edges. In this study, we used the Canny edge detection algorithm to perform image segmentation and binarization of the original human body image. The Gaussian smoothing operator is used for image de-noising. Finally, the ACAFCM algorithm is used to extract the image edge contour. The process flow is shown in figure 2.

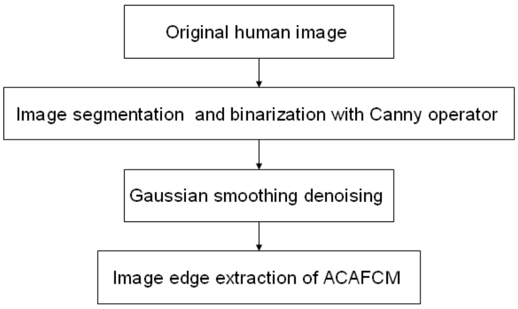

Figure 2. Flowchart of image processing

III. Image Capture And Preprocessing

A. Image Capturing

There are a lot of methods of image processing [19-21]. In this paper, three images of a young woman's body were captured to obtain the human body dimensions: the front image, the side image in the standing position, and the side image in the sitting position.

Figure 3. Captured human original images with three points of view

B. Image Preprocessing

The Canny algorithm is used for image segmentation, binarization, and de-noising in order to simplify the image color and noise information and to facilitate the image edge extraction.

The image after preprocessing is shown in figure 4.

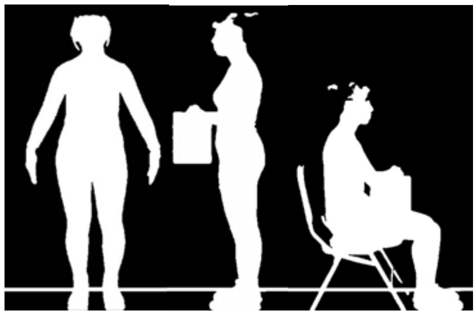

Figure 4. After preprocessing

IV. Result Of Image Edge Extraction

A. The Result of Image Edge Extraction with ACAFCM

The ACAFCM algorithm is used to extract the edges in the human body image after preprocessing. The edge contours of human body that were obtained from the image are showed in figure 5.

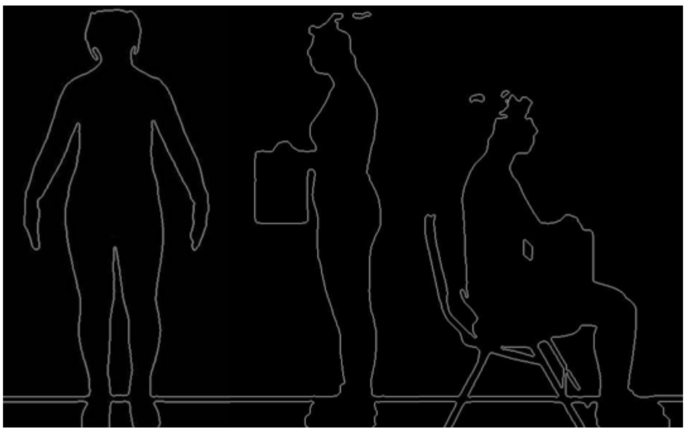

Figure 5. Result of image edge extraction using ACAFCM algorithm

B. Comparing the Results of Image Edge Extraction

The edge contours resulting from the Canny algorithm are fuzzy and discontinuous with missing parts, as shown in figure 6. On the other hand, the edge contours resulting from the ACAFCM algorithm are clear and continuous, as shown in figure 5. The ACAFCM algorithm is clearly superior to the Canny algorithm in performing edge extraction on a human body image.

Figure 6. Result of image edge extraction using Canny algorithm

V. CONCLUSIONS

To obtain highly accurate anthropometric measurements, an effective image edge extraction technology is needed to extract the edge contours from a human body image. We combined two well-known algorithms to develop a new and effective image edge extraction technology.

In our experiment, images of a young woman's body were captured and preprocessed. Then the ACAFCM algorithm was used to extract the edges from the images.

The results of the ACAFCM algorithm and of the Canny algorithm were compared, and the ACAFCM algorithm proved to be a better edge extraction method.

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