Human Object Extraction Using Nonextensive Fuzzy Entropy and Chaos Differential Evolution

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Abstract

Human object extraction from infrared image has broad applications, and has become an active research area in image processing community. Combined with chaos differential evolution (CDE) algorithm and morphological operators, a novel infrared human target extraction method is proposed based on nonextensive fuzzy entropy. Firstly, the image was transformed into a fuzzy domain by fuzzy membership function, and the image nonextensive fuzzy entropy was constructed. Then, the image was segmented by thresholding based on the maximum entropy principle and the pseudoadditivity rule of nonextensive entropy. In order to reduce the search time of optimal threshold selection, the CDE algorithm was presented. Finally, the object was extracted using morphological operators to denoise, fill cavity on the threshold segmented image. Experimental results show that the proposed method is efficient and requires less computation time.

Keywords: *Infrared image processing; Human object extraction; Nonextensive fuzzy entropy; Chaos differential evolution; Morphological operator*

1. Introduction

Human object detection has widely application in real life, such as auto auxiliary driving, anti-terrorist, battlefield military applications. Currently, the technologies of human targets detection based on visual image and infrared image have obtained extensive attention of researchers [1]. Due to the complexity of the realistic environment, the task of human targets detection is a very large challenge. Since the imaging equipment is not adapted to night, rain, snow, fog such bad weather environment, the application range of technologies based on visual image is limited extremely. The infrared imaging technology has the nature immunity to bad weather environment, and the cost of infrared imaging equipment is reduced continually recent years. The study of human targets detection based on infrared image is getting more and more researchers' attention [1].

The key issue of human targets detection is the extraction of region of interest (ROI) of image [1]. Generally, the human body is regarded as a brightness field in infrared image; the characteristic of human body is described by the information of image gray value. However, due to the imaging characteristics of the infrared technology, the grayscale scope of human body in infrared image is less than visual image, and poor quality, low resolution, low contrast, vague, less feature points, and lacks of texture information. So, the task of locating the ROI's position of human body accurately is a rather difficult work in infrared image. Generally, the method of ROI extraction is image segmentation. Considering the real time requirement, the image thresholding method is usually adopted in infrared image processing [2, 3]. In image thresholding, the entropy-based method is a popular and important technology [4-6]. Since it has solid physics foundation, the entropy-based thresholding methods have obtained application widely.

In infrared image, the target pixels and background pixels are often in a state of mixture, *i.e.*, the border of target and background is very vague. So, the separation of target and background is very difficult. Fuzzy sets theory is an effective tool to handle problem with fuzziness. In image segmentation field, some fuzzy entropy methods have been presented by many researchers [7-9]. On the problem of infrared image segmentation, entropy-based and fuzzy entropy-based methods were proposed by [2] and [3]. However, the effect is not good when these methods are applied to human target extraction from infrared image.

Inspired by concept of multidimensional fractal and structure, a generalized entropy form was presented by Tsallis [10]. In many reference, the entropy is called nonextensive entropy or Tsallis entropy [11-13]. Some studies indicate that the image is a classical nonextensive physical system [11-13]. For image segmentation, there are several methods based on nonextensive entropy have been proposed by researchers [12, 13]. Since these methods not only consider the characteristics of image target and background, but also consider the relationship between them, so the segmented results obtained by these methods are better than that obtained by those traditional entropy methods [12, 13].

Considering the nonextensive and vague characteristics of infrared image, a method combined with morphological operator is presented in this paper for human targets extraction from infrared images. The work of image segmentation in fuzzy domain involves the parameters optimization of membership functions. This process is very time-consuming. In order to reduce the computation time, a differential evolution [14] algorithm embedded chaos search [15] is proposed for optimal threshold selection. Finally, the compared experiments between the proposed method and the other methods are executed on real infrared human images. The experimental results show that the proposed method is effective.

The remainder of this paper is organized as follows. The principle of object extraction using nonextensive entropy, fuzzy set theory and morphological operation is given in Section 2. In Section 3, the chaos differential evolution algorithm is proposed to tackle the problem of selection of the optimal parameter combination of fuzzy membership function. Section 4 reports our experimental results for real-world infrared human images, including comparative study between the proposed method and other two new object extraction methods. Finally, the conclusions are drawn in Section 5.

2. The Principle of Object Extraction

In this section, we give brief descriptions about the nonextensive entropy and fuzzy sets theory for object extraction.

2.1. Nonextensive Entropy

Let X denote a random variable taking values in finite set space $\Omega=\{x_1, x_2, \ldots, x_n\}$ according to a probability distribution P_X. For a parameter $q\geq 0$, the nonextensive entropy, denoted $S_q(X)$, is defined as follows [10]

$$S_q(X)=\frac{1}{q-1}\left(1-\sum_{i=1}^{n}p_i^q\right) \tag{1}$$

which includes Shannon's entropy as a special case when $q\rightarrow 1$.

For two independent random variables X and Y, Shannon entropy $S(X)$ has an additivity, *i.e.*, $S(X\times Y) = S(X) + S(Y)$. However, for the nonextensive entropy $S_q(X)$, it has a pseudoadditivity [10]

$$S_q(X\times Y)=S_q(X)+S_q(Y)+(1-q)S_q(X)S_q(Y) \tag{2}$$

2.2. Image as a fuzzy set

Let I be an image with size $m\times n$ and L gray levels. Let $f(x,y)$ be the gray level at location (x,y) in I, where $x=1,\ldots,m$, $y=1,\ldots,n$, and $f(x,y)\in G=\{0,1,\ldots,L\text{-}1\}$. The gray levels histogram H about I can be calculated by $H=\{h(i)|i=0,1,\ldots,L\text{-}1\}$, where $h(i)=n_i/(m\times n)$, n_i is the total number of pixels with gray level i in image I.

When image segmented by thresholding in fuzzy domain, the membership function that transform image into fuzzy domain are introduced. Let $\mu_b(i)$, $\mu_f(i)$ denote the values of membership functions of background and foreground, and $\mu_b(i)+\mu_f(i)=1$. In image thresholding, the class of gray level i is determined by its value of membership. There exist several membership functions that can be used to image fuzzy thresholding, such as triangular functions, Z-shaped function, S-shaped function, *etc*. In our experiment, the Z-shaped and S-shaped functions can better represent the vague characteristics of gray levels on infrared image background and foreground. So, the Z-shaped and S-shaped functions are adopted as the membership functions of background and foreground, *i.e.*,

$$\mu_b(i)=\begin{cases}1, & i\leq a\\ 1-\dfrac{(i-a)^2}{(c-a)(b-a)}, & a<i\leq b\\ \dfrac{(i-c)^2}{(c-a)(c-b)}, & b<i\leq c\\ 0, & i>c\end{cases} \tag{3}$$

$$\mu_f(i)=\begin{cases}0, & i\le a\\ \dfrac{(i-a)^2}{(c-a)(b-a)}, & a<i\le b\\ 1-\dfrac{(i-c)^2}{(c-a)(c-b)}, & b<i\le c\\ 0, & i>c\end{cases} \tag{4}$$

Where a, b and c are the membership functions' parameters that determine the scope of fuzzy area, and $0\le a\le b\le c\le L-1$, obviously, $\mu_f(i)=1-\mu_b(i)$.

2.3. Image nonextensive fuzzy entropy

When image is transformed to fuzzy domain, according to principle of nonextensive entropy, the nonextensive fuzzy entropy of image background and foreground can be defined as follows

$$S_b^q=\frac{1}{q-1}\left(1-\sum_{i=0}^{L-1}\left(\frac{\mu_b(i)\cdot h_i}{P_b}\right)^q\right) \tag{5}$$

$$S_f^q=\frac{1}{q-1}\left(1-\sum_{i=0}^{L-1}\left(\frac{\mu_f(i)\cdot h_i}{P_f}\right)^q\right) \tag{6}$$

Where

$$P_b=\sum_{i=0}^{L-1}\mu_b(i)\cdot h_i \tag{7}$$

$$P_f=\sum_{i=1}^{L-1}\mu_f(i)\cdot h_i \tag{8}$$

According to the definition of fuzzy membership function, it can be see that $P_b+P_f=1$.

2.4. Image segmentation

If the ROIs is extracted by thresholding, the appropriate threshold point t^* must be found firstly, and then the image segmented by the threshold t^*, *i.e.*,

$$\bar{f}(x,y)=\begin{cases}0, & f(x,y)\le t^*\\ 1, & f(x,y)>t^*\end{cases} \tag{9}$$

According to the pseudoadditivity of nonextensive entropy and the maximum entropy principle [10] of image segmentation, the optimal parameter combination of fuzzy membership function can be determined by

$$(a^*,b^*,c^*)=\arg\max_{a,b,c}\left[S_b^q+S_f^q+(1-q)\cdot S_b^q\cdot S_f^q\right] \tag{10}$$

When optimal parameter combination is found, the optimal threshold t^* can be computed by solving $\mu_b(i)=\mu_f(i)$, *i.e.*,

$$t^*=\begin{cases}a+\sqrt{\dfrac{(c-a)(b-a)}{2}}, & (a+c)/2\le b\le c\\ c-\sqrt{\dfrac{(c-a)(c-b)}{2}}, & a\le b\le (a+c)/2\end{cases} \tag{11}$$

In infrared human image thresholding, the pixels that the gray value is larger than t^* are processed as target pixels.

2.5. Object extraction

Due to the parts of human body have different intensity of heat radiation, the broken, fragmented phenomena often appear on human object after the infrared image segmented by thresholding. In addition, because of the interference of background heat source, noisy points are often exists in the segmented image also. In order to avoid these, we use morphological operation to achieve the goal of human target extraction after image thresholding. That is, the morphological operation [16] is used to remove isolated noisy pixel points firstly; then the open and close operation are used to connect the fragmented parts of target; after that, the fill operation is used to filling the cavity; finally, the structuring element of 3×3 is used to perform dilation operation for segmented image.

3. Chaos Differential Evolution Algorithm

From the description previously, we can see that the process of seeking the optimal threshold involves the optimization of fuzzy membership function's parameters. If we adopt the method of exhaustion, the process will spend much computing time. The differential evolution (DE) [14] algorithm is a relatively novel optimization technique to solve numerical-optimization problems. The algorithm has recently become quite popular in the machine intelligence and cybernetics community, and has, in many cases, been shown to be better than the GA or other population based optimization algorithms [17, 18]. However, DE does suffer from the problem of premature convergence to local optima [17, 18]. Chaos is a bounded unstable dynamic behavior that exhibits sensitive dependence on initial conditions and includes infinite unstable periodic motions in nonlinear systems [15]. Although it appears to be stochastic, it occurs in a deterministic nonlinear system under deterministic conditions. Due to the easy implementation and special ability to avoid being trapped in local optima, chaos has been a novel optimization technique and chaos-based searching algorithms have aroused intense interests [19]. In order to search the optimal threshold fast, a chaos DE algorithm is presented to solve the problem of parameters optimization.

In this paper, the well-known logistic equation is employed for construction hybrid chaos DE. The logistic equation is defined as follows [15]

$$x_{t+1} = r \cdot x_t \cdot (1 - x_t) \tag{12}$$

Where x is the chaos variable, $0 \le x_t \le 1$; t is the times of iteration, t=1,2,…; and r is the control parameter. It is easy to testify that the system is entirely in chaos situation when r=4 and the chaos space is [0, 1]. When the chaos embedded DE algorithm is applied to search the optimal threshold for image segmentation, the chaos variable x_t must be mapped to the space of gray level firstly, *i.e.*,

$$g = g_{\min} + (g_{\max} - g_{\min}) \cdot x_t \tag{13}$$

Where g_{min} and g_{max} denote the minimum and maximum of gray levels value in image. According to the principle of DE, the chaos embedded DE algorithm which used to search the optimal threshold based on the image nonextensive fuzzy entropy is described as follows.

Step 1: Set the number of population size P, maximum iteration it_{max}, count of iteration it=0.

Step 2: Initialize the individual X_i of parameter vector (a,b,c) according to Eq. (12) and (13), and evaluate it according to Eq. (10).

Step 3: For i=1 to P

3.1 generate two new chaotic individuals of fuzzy membership function parameters according to Eq. (12) and (13), *i.e.*, X_{new1} and X_{new2}.

3.2 generate the mutant vector D_i as follows.

$$D_i = X_{best} + F \cdot (X_{new1} - X_{new2}) \tag{14}$$

3.3 generate the trail vector T_i to implement crossover operation to increase the diversity of the population as follows.

$$T_{ij} = \begin{cases} D_{ij}, if\ (rn \le CR) or\ (j = d) \\ X_{ij}, otherwise \end{cases} \tag{15}$$

3.4 evaluate T_i according to Eq. (10), and implement selection operation as follows.

$$X_i = \begin{cases} T_i, if\ T_i\ yields\ better\ fitness\ value\ than\ X_i \\ X_i, otherwise \end{cases} \tag{16}$$

Step 4: Let it=it+1 and go to Step 3 if the desired number of generations is not reached.

In above algorithm, X_{best} denotes the individual with maximum of fitness value in current generation. F is a uniformly distributed random variable with range [0, 1]. In this paper, the value of F is determined by

$$F = 0.5 \times (1 + rand(0,1)) \tag{17}$$

Where $rand$(0,1) denotes a uniform random number with range [0, 1]. In Step 3.3 of above algorithm, rn is a number generated by $rand$(0,1). CR denotes the cross probability of DE algorithm, in this paper it is generated by Eq. (18).

$$CR = CR_{\min} + (CR_{\max} - CR_{\min}) \cdot \frac{it_{\max} - it}{it_{\max}} \tag{18}$$

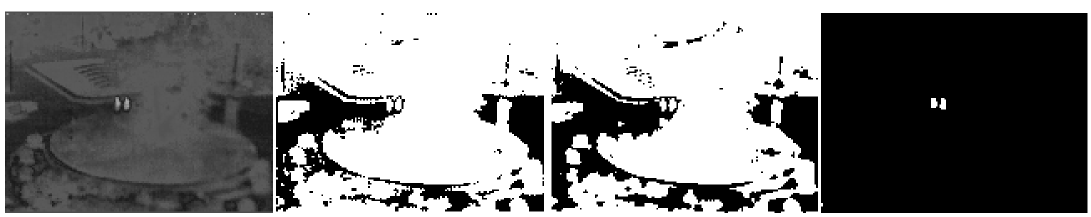
Where CR_{max} and CR_{min} denote the maximum and minimum of cross probability CR. Variable d in Step 3.3 is an integer selected from [1,…,D] randomly. D denotes the dimension of individual vector, j denotes the jth component and D=3 in this paper.

4. Experimental Results and Analysis

We implement the proposed method in Matlab with a Interl(R) Core(TM) Duo CPU T8100 2.1GHz and 2GB RAM. In our experiments the population size P of the proposed CDE algorithm is set to 30, the number of maximum iteration it_{max}, the maximum cross probability CR_{max} and the minimum cross probability CR_{min} are set to

100, 0.9 and 0.1, respectively. The approach presented by [3] as a new method applied to extraction of infrared object claims that its performance is better than several classical entropy-based and fuzzy entropy-based methods. The approach presented by [20] as a new image segmentation method claims that its performance is better than some classical image segmentation methods, such as Otsu method [21], minimum error thresholding method [22], entropy-based method [5, 13] and an improved fuzzy C-mean algorithm [23]. So, to verify the validity of the proposed method, the two methods were compared with the proposed method. For convenience sake, the method of [3] is denoted by “Tao method” and the method of [20] is denoted by “Guo method” in this paper.

For demonstrating the adaptability of the proposed method, the infrared images for test is adopted from different frame sequences at different scenes. The infrared videos applied in our experiments all come from some real scenes. Due to space constraints, three frame images come from different sequences of infrared frame image are applied to demonstrate the performance of methods compared with each other. The three frame images are shown in Figures 1(a)-3(a).

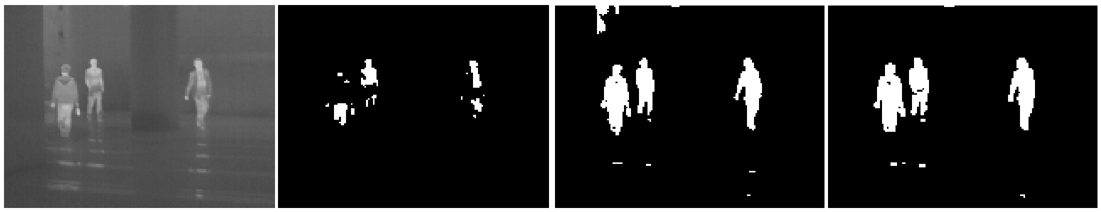


(a) (b) (c) (d)

Figure 1. IR1 and the segmented results by different methods: (a) Original image, (b) Tao method, (c) Guo method, (d) The proposed method

The original image of Figure 1(a) and 2(a) come from infrared video sequences captured by ThermoVision A40M. Figure 1(a) is the 11th frame image of a video sequence on an outdoor green space of a residential area. The shooting time is afternoon of a day in the autumn. There is some breeze and little mist in that day. On this scene, the camera lens of thermal imaging system is far from the target position. Figure 2(a) is the 145th frame image of a video sequence on entrance of a building. The shooting time of this video is late afternoons of a day in the end of spring and the beginning of summer. The weather of this day is hot. On this scene, the camera lens of thermal imaging system is not far from the target position. The size of Figure 1(a) and 2(a) is 320×240. Figure 3(a) is the 13th frame image of a sequence come from OSU Thermal Pedestrian Database [24]. The size of Figure 3(a) is 360×240. For convenience, the three images mentioned above are named "IR1", "IR2" and "IR3" in this paper.

Since the lens of the thermal imaging system is far from the target position and scene is more complicated, the image of Figure 1(a) is blurry and the target is small. From Figure 1, we can see that the target can be extracted effectively when the image is processed by the proposed method (q=0.1), whereas the target can't be separated from the background completely when the image of Figure 1(a) is processed by Tao and Guo methods.



(a) (b) (c) (d)

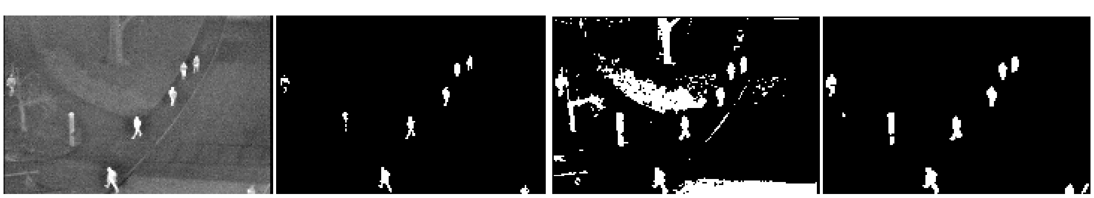
Figure 2. IR2 and the segmented results by different methods: (a) Original image, (b) Tao method, (c) Guo method, (d) The proposed method

When human body is nearer to the lens, the gray level of human targets in infrared image will lead to an uneven distribution because the radiant heat of parts of human body is different. The image of Figure 2(a) illustrates the phenomenon. From Figure 2, we can see that there is obvious phenomenon of fracture, broken in the results obtained by Tao method on human targets. The targets obtained by Guo method is detected well, however the only fly in the ointment was the more noise exist in the results. In the results of the proposed method (q=2), the targets are integrated, distinct and leave few noise in the segmented image compared with other methods.

Figure 3 illustrates the results on benchmarks image from [24]. For the results obtained by Tao and Guo methods, there are same problems as appeared in Figure 2 while the outlines of targets are integrated and clear in the result obtained by the proposed method (q=2).

Since the nonextensive fuzzy entropy not only has the ability to tackle fuzzy information but also consider the correlation between the object and background in task of image segmentation, it has better ability in image processing. This conclusion also can be concluded from above experiments.

Generally speaking, it has high real-time performance requirement in infrared image processing. In order to obtain the fast processing speed, the chaos differential evolution (CDE) algorithm is proposed to carry out the task of threshold selection in image segmentation in this paper. The ant colony optimization (CAO) algorithm is used in Tao method [7] for threshold selection. The approach [20] presented by Guo and Cheng is a pixels clustering image segmentation method based on neutrosophic set theory. Table 1 lists the average CPU time of 50 independent running on test images of different methods. In addition, the exhaustive search algorithm based on the proposed method is implemented, and the CPU times for test images were recorded in Table 1 also.



(a) (b) (c) (d)

Figure 3. IR3 and the segmented results by different methods: (a) Original image, (b) Tao method, (c) Guo method, (d) The proposed method

From Table 1, it can be seen that there is faster convergent rate of the proposed method than other three methods. The CPU time required for the proposed method is only 0.25 seconds for images with 256 gray levels. It is far below the time requirement of exhaustive search method, and is less than that of other two methods also. For Guo method, the CPU time is sensitive to the image size. When the image size enlarged from small size, the time of Guo method is increased dramatically.

Table 1. Time performance comparison for four different methods (second)

Image(Size)	Tao method	Guo method	Exhausted	Proposed
IR1(320×240)	0.2565	4.8223	1.7392	0.2341
IR2(320×240)	0.2641	5.9692	19.3810	0.2419
IR3(360×240)	0.2873	41.9468	215.7645	0.2592

Because the search results obtained by population optimization algorithm have certain randomness, we repeated experiments to test the search stability of the DE and the proposed CDE methods. The average results of optimal threshold values of DE and CDE methods in 50 repeated, independent experiments are shown in Table 2. Meanwhile, the optimal threshold values obtained by exhaustive search algorithm applied the segmentation principle of the proposed method are also shown in Table 2.

Table 2. Comparison of optimal thresholds

Image	Exhausted	DE	CDE
IR1	127	123	127
IR2	122	119	122
IR3	151	145	151

As can be seen from Table 2, the CDE method can give the similar optimal thresholds as that of the exhaustive search. In contrast, the results obtained by DE method deviate greatly from the results of exhaustive search. Since the DE algorithm is easy converges to the local minima, the deviation to the global optimal value will exist inevitably. However, for the propose method CDE, the chaos search is embed into DE, the shortage of DE has been overcome well and the global search ability is improved greatly.

5. Conclusions

In this paper, the method of infrared human object extraction is proposed based on the nonextensive fuzzy entropy and morphology operators. In this method, not the fuzziness of infrared image but also the relation between object and background, *i.e.*, the nonextension characteristics of image are all considered for image segmentation. Additionally, we have designed a chaos differential evolution strategy to find the optimal combination of all the parameters of fuzzy membership functions. The experiment results show that the implementation of the proposed nonextensive fuzzy entropy by CDE has effective search performance to finding the optimal threshold for image segmentation. The human targets that extracted by the proposed method from infrared images are integrated, clear and therefore, the proposed method is suitable for real-time vision applications, such as automatic target recognition, tracking, *etc.*

Acknowledgements

The authors wish to thank the anonymous referees for the valuable comments and suggestions which helped to improve this paper. This research is partially supported by the Scientific Research Fund of Hunan Provincial Education Department, China (Grant No. 11C0913), the Young Core Instructor Foundation of Hunan Provincial Institutions of Higher Education of China, the Doctor Scientific Research Startup Project Foundation of Hunan University of Arts and Science, China, and the Planned Science and Technology Project of Hunan Province, China (Grant No. 2010GK3021).

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