Acta Technica 62, No. 1A/2017, 91–98

New approach for detection of giant panda head in wild environment[1]

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Abstract. Video surveillance technology has been widely used for protection of pandas in wild environment, however, the automatic detection method of panda in the image was not efficient so far. So in this paper an improved approach of head detection of giant panda in the image was proposed. First image segmentation based on gray threshold was used to detect candidate region of giant panda in the image. Then a new kind of head region detection method was introduced, which was able to cluster giant panda head region of different sizes along the skeleton. Finally, standard data sets were used to train a fuzzy neural network for the detection of head region. The experiment results showed that the improved method was efficient and accurate to detect the head region of panda.

Key words. Panda head detection, skeleton extraction, k nearest neighbor (KNN) clustering, fuzzy neural network.

1. Introduction

A variety of images are captured in the video surveillance system for panda in the wild environment, but only the images with panda are necessary. At present, an abundance of algorithms in the human face detection are available, and their accuracy are more than 90 % for human detection. Viola et al. applied some algorithms, representations, and insights which are quite generic and may well have broader application in computer vision and image processing [1–3].

However, the animal face have more variation than human face [4–6], and animal face detection is more difficult than detecting human face. Some researchers proposed a cat head detection method, which well exploited the shape and texture information by extracting two kinds of patterns aligned by eyes and tips of ears [7–9].

[1]This research is supported by the Fundamental Research Funds for the Central Universities (NO.2015ZCQ-GX-03).

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In the field of giant panda head detection, Chen et al. proposed two algorithms for giant panda head detection: 1) Detect panda facial region based on topology modelling; 2) Find the head region around the limb areas. Zhang et al. used haar of oriented gradient (HOOG) as their features and proposed two joint detection approaches to detect giant panda and other cat-like animal's head, which all have distinctive ears and frontal eyes [10].

In this paper, we proposed a new algorithm focused on the detection of giant panda's head, which firstly separated the background and the giant panda by segmentation of gray scale image, Secondly located its head from the binary image through the skeleton extraction technology. Thirdly based on the skeleton line or the surrounding region skeleton line, used two-stage KNN clustering method contrasted images in training set to detect the existence of giant panda's head in images. In the refining stage, a training set was established to detect the head based on fuzzy neural network. Our approach offers two advantages: 1) A rapid preliminary scanning, which due to fast threshold segmentation and a scan method based on skeleton line to reduce search region; 2) Fuzzy neural network promoted the accuracy after the two-stage KNN clustering method.

2. Methodology

The proposed algorithm is schematically depicted in Fig. 1.

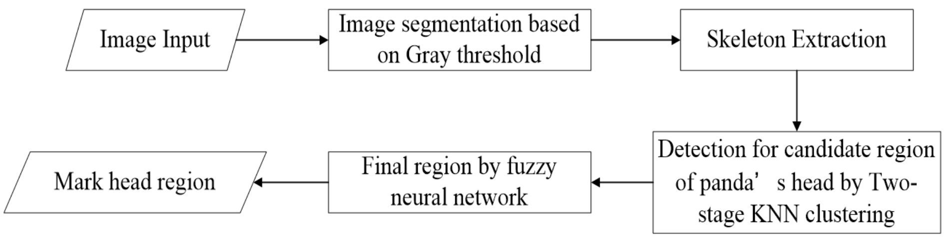

Fig. 1. Flow-chart of proposed algorithm

2.1. Image segmentation

For a giant panda image, its most prominent feature is the hair color. In addition to the region of mild change caused by stains, shadows and illumination changes, the giant panda body is mainly made up of pure black and pure white. Gray space is made of pure black, pure white and the different levels of gray between them, and interval of gray image is [0,255]. By converting RGB images into gray images, we could well describe its color feature. This study used a segmentation algorithm based on gray space, which first identified respectively the white and black areas in the body of the panda, and then separated it from the background.

According to the histograms of images, both the black hair and white hair of giant panda had a centralized gray value, and the value of images in database also had a certain intersection with the black and white hair.

Threshold segmentation was applied to convert a gray image to binary image. As presented in formula (1), $f(x, y)$ is the original image. Grey value T was used as the threshold after being found out in the $f(x, y)$. The image was segmented into two parts: the gray value of the pixels that are greater than or equal to the threshold were set to 1, while the ones that were less than or equal to the threshold were set to 0. After the threshold operation, the image would be turned into a binary image $g(x, y)$.

$$g(x,y) = \begin{cases} 1 & f(x,y) \geq T \\ 0 & f(x,y) < T \end{cases} \tag{1}$$

Integrated the above properties, the preliminary segmentation of the panda region from the image could be completed. Experimental results are shown in Fig. 2. Once selected the panda region, we scanned for the head of the animal, which had the most obvious features.

Fig. 2. Results of segmentation: left pair–original images, right pair–segmented images

2.2. Skeleton extraction

In most cases, the panda's head could be found near the skeleton after the segmentation of the panda body region. There were two parts of the segmentation:

1) First, extract the skeleton from the separated region [6]. The result is presented in Fig. 3c. However, in some images in which the segmented region was relatively round and smooth, and the head was located near the edge of the selected region, instead of the skeleton. In this case, a second skeleton extraction method was needed

to complement the mentioned one.

2) As shown in Fig. 3d, we retained the largest white region, where the value was 1, in the binary image. Subtract the largest white region in its centroid location by an area in proportion p. In this paper, the value of p was 40 %. The computation formula of p is as follows:

$$p = 1 - \sqrt{\frac{\text{areaofpandaheads}}{\text{areaofwholepandabody}}}\,. \tag{2}$$

After that, we could get a ring region for the skeleton extraction. Synthesizing the two skeleton extraction methods, we could locate the giant panda head along the bone in different specific cases.

Since then, we adopted the two-stage KNN clustering method to locate the panda's head, comparing the images in training set. The Skeleton extraction method is implemented in the following:

Step 1: Use bwmorph function to extract the skeleton from the binary image, stored as S1.

Step 2: Calculate binary image in each region and locate the centroid of the largest white region.

Step 3: Subtract the largest white region in its centroid location by 30 % area of itself.

Step 4: In the new ring area, using bwmorph function to extract the skeleton, stored as S2.

Step 5: Get S as the superposition of S1 and S2.

Step 6: with the interval of 20 pixels, set the points on the bone S as the center of test blocks. The side length of various sizes blocks can be 50, 100, 150 and 200 pixels.

2.3. Two-stage KNN clustering method

After getting the blocks of various sizes of the image, they would be compressed to 50 ×50 pixels. A two-stage KNN clustering method was proposed to cluster the panda head. A Training set needed to be established, and the training images could be divided into several categories, such as head, head around images, the background, etc. The mean value of the compressed blocks were recorded as u whose computation formula is as follows:

$$u(x, y) = \frac{1}{8 \times 8} \sum_{i=0,j=0}^{7,7} I(x+i, y+j)\,. \tag{3}$$

Here, I is the input block image and x and y are the coordinations of the pixel. Search for the K nearest training neighbors to the test pattern was based on distance measure with the feature u the number of each categories were recorded as $c1$, $c2$, $c3$. Furthermore, Euclidean distance was calculated by pixel block between the test block and the training sample, and denoted as d. Search for the $K/2$ nearest

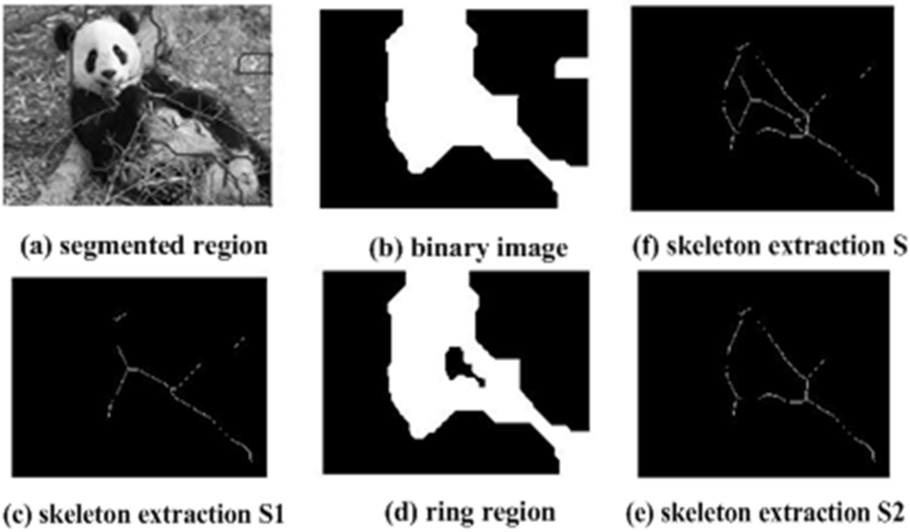

Fig. 3. Skeleton extraction result

training neighbors to the test pattern used the distance measure with the feature d. The values of distance of each category were recorded as $d1$, $d2$, $d3$. Formula (4) was used to calculate each confidence of categories

$$E = ci + 0.5 * di\,. \tag{4}$$

Here, E is the parameter used to determine whether the block was the head regions of giant pandas. After implementing two-stage KNN clustering method, multiple scale blocks close to the head regions were filtered. But most of the smaller blocks were within the border of faces, rather than included the whole face. So the blocks that were two levels smaller than the largest scale were unnecessary. For example, if the largest block was 200×200 pixels, so only two kinds of scales, 200×200 pixels and 150×150 pixels, would be adopted to detect the candidate head region, rather than other scales, such as 100×100 pixels and 50×50 pixels. The step of scale is 50×50 pixels is used in this research. They would be qualified as neural network input test images. Head candidate screening region diagram is shown in Fig. 4.

2.4. Detection

Although the areas of some candidate panda heads had been filtered, the accuracy was not high due to two reasons. First, the accuracy for KNN clustering method was not satisfactory. Second, there were too many outputs. In the next step, there should be a further recognition, in order to filter out unnecessary results, and to determine a final area of the head.

Fuzzy neural network identification methods were applied to some candidate panda images to identify the head zone. In the sample collecting stage, we built up another training set to store the typical head samples of pandas in various poses including the background [11, 12]. The fuzzy neural network was implemented to filter the head of giant panda in various poses and angles from the background. The panda's head area after processing by the fuzzy neural network is depicted in Fig. 5.

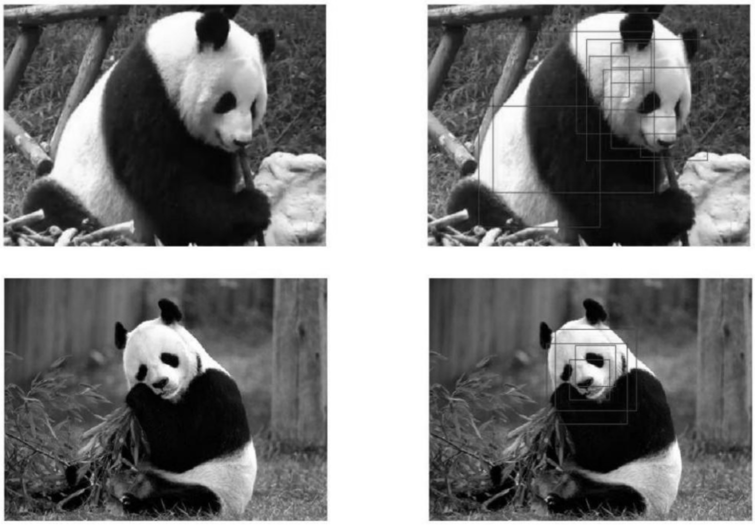

Fig. 4. Head candidate screening region diagram: left part–original images, right part–head candidate region

Fig. 5. Head area after fuzzy neural network

3. Result analysis and discussion

For all the output results of the identification of the giant panda head, they needed to be further integrated through the center position and figure block size, to determine a final head position and size. The giant pandas images in various cases were processed to test robustness of the algorithm. There were two items to evaluate:

1) Pose of the giant pandas, including looking front, side and down.

2) The distances of the giant pandas, it could be detected in different distances.

To measure the accuracy, 3000 wild giant panda images were collected. 2000 of them are frontal faces, and others are side face. Half of the images were taken over a long distance, and the other half were shot at close range. One thing to note is the images which were chosen were in the wild, so the backgrounds are almost close to green. The algorithm, for various cases of the giant panda heads, had very good detection effect. Short distance will make a positive influence in the detection effect. Fig. 6 shows the experimental results, and the giant panda head was boxed by red rectangular.

Fig. 6. The giant panda head region detection under different distances

4. Conclusion

In this paper a novel approach of detecting the head of panda in the images in wild environment was presented. The image segmentation method based on gray threshold was used to detect regions in the image that were candidate regions for giant pandas. The candidate regions of panda's head were detected by two stage KNN clustering method after extracting the skeleton of above result images. Finally, standard data sets are used to train a Fuzzy neural network for the detection of head area. The amount of experiments were conducted to prove the proposed algorithm was useful and accurate. Furthermore, ongoing work aims to be able to detect pandas in different complicated environments.

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Received April 23, 2017