Shape Feature Extraction Methods of Rodents in the Field Based on Machine Vision

Deli Zhu¹,², Bingqi Chen¹,*, Liliang Han³ Yong Wang³, Chaojie Wei⁴, Jie Feng¹

¹College of Engineer, China Agriculture University, Beijing 10083, China
²College of Computer and Information Science, Chongqing Normal University, Chongqing 401331, China
³Key Laboratory of Agro-ecological Processes in Subtropical Region/Dongting Lake Station for Wetland Ecosystem Research, Institute of Subtropical Agriculture, Chinese Academy of Sciences, Changsha 410125, China

* Corresponding author. College of Engineer, China Agriculture University, Beijing, 100083; China. Key Laboratory of Agro-ecological Processes in Subtropical Region/Dongting Lake Station for Wetland Ecosystem Research, Institute of Subtropical Agriculture, Chinese Academy of Sciences, Changsha 410125, China.

E-mail address: fbcbq@163.com; wangy@isa.ac.cn

Abstract. In order to obtain the shape features of rodents from the field, a feature extraction scheme based on machine vision was proposed. We design an experimental device with a camera. The camera placed on the top of the device to get the rodent image. After thresholding rodent image based on the global value, we get the binary image, and then the morphological erosion and dilation operation are used to denoise, and the contour are detected by the 8 adjacent pixels of a point. Chain code analysis method is used to track the contour. Multi-contour tracking extraction method is used to remove the non-rodent region. Based on the shape of the rodent tail that is slenderer than the body, we split the rodent's tail from the body on the precise contour image. The length of the tail, the length of the body, the height of the body, the proportions of the tail and the body are extract based on contour analysis. Experiments show that this method can extract shape features of rodents accurately. It can provide basic data for analyzing the life habits and population evolution of field rodents.

1. Introduction

The rodent is a harmful animal for agricultural production. It steals seeds, bites seedlings and does a lot of harm to crops. It also digs holes under the root of the trees. It affects the growth and development of trees. What is more serious is that it leads to the invasion of pests and microorganisms, causing pests and diseases, and even the death of trees and crops.

Traditional animal observation is usually done by artificial vision. It requires continuous and uninterrupted observation and recording. This method is not only time-consuming and laborious but also difficult to quantify so many parameters. The reliability of the recorded data is low.

In recent years, with the development of computer technology, researchers have studied the behavior and posture of rodents with video recording and computer vision. Rousseau distinguishes the
typical behavior of rodents combined with the activity model (Rousseau J B I, Lochem P B A V, 2000.). Some researchers constructed the feature vector with the Fourier descriptors of the rat contour, and classify the posture with neural network (Rousseau J B I, Lochem P B A V, et al, 2000). Some researchers identify 3 kinds of rodents’ behaviors which are movement, stillness and decoration with motion analysis and contour spectrum analysis (Ayelet A B, Hagit D, Yoseph A, 2016).

Ming Chang in Zhejiang University of China proposed two methods to distinguish the body states of rodents. The first one is extracting common body contours of the rat and constituting a vector feature library. Then the body state image of rodent is taken by a camera, and compared with the shape of the vector library. The second is extracting the target invariants in the rodent body image to build the neural network and identifying the various postures of rodents (Zhang M, Zhang H Y, Zheng X X, 2006).

In this paper, an experimental scheme is designed for automatically extract shape features of rodents based on computer vision. A device with a camera is designed for this purpose. The camera placed on the top of the device to capture the rodent image. After thresholding rodent image based on the global value, the binary image is obtained, and then the morphological erosion and dilation operation are used to denoise, and the contour points are detected by the adjacent 8 pixels of a point. 8 connecting chain code analysis method is used to track the contour. Multi-contour tracking extraction method is used to remove the non-rodent region. Based on the shape of the rodent tail that is slenderer than the body, the rodent's tail is split from the body on the precise contour image. The length of the tail, the length of the body, the height of the body, the proportions of the tail and the body are extract based on contour analysis.

2. Materials and methods

2.1 Acquisition of experimental materials

In this experiment, the acquisition equipment provided by professional manufacturer was used to acquire the videos of field rodents. When the rodents run into the box, the camera located above the box is triggered to collect the videos, and then the videos are transmitted to the image processing terminal by a 4G transmission device. The main structure of the image acquisition terminal is shown in Figure 1.

![Fig. 1 experimental device](image)

Note: 1. Mobile power 2. Power cable 3. Camera 4. 4G image transmission equipment 5. Processing computer 6. Network devices for receiving

2.2 Image segmentation method based on global threshold

Rodent target must be extracted from the background before feature extraction. Because the effect of the target extraction has a direct impact on the results of the subsequent analysis. It has great significance in image processing and recognition of rodents’ species. In this study, the global threshold method was used to segment object from background.
As a result of image acquisition, the rodent target have a good distinction with background. Figure 2 (a) is grey image of acquisition result. Figure 2 (b) is the histogram of Figure 2 (a). As can be seen from the figure, the statistics of pixel values has two obvious peaks. The image can be segmented effectively with a suitable threshold value. In this paper, the following algorithm is used to choose the threshold automatically according to the histogram of grey rodent image:

1. Select $G$ as the initial segmentation threshold, which is the average pixel value of the image.
2. Segment the image with $G$. This will produce two pixel sets: One is made up of all pixels which are greater than $G$. Name this group as $I_1$. The other group is made up of all pixels whose value is less than or equal to $G$. Name this group as $I_2$.
3. Calculate the average value in $I_1$ and $I_2$, represented by the variable name $m_1$ and $m_2$ respectively.
4. Formula (1) is used to calculate the new threshold.

$$G = \frac{1}{2} (m_1 + m_2)$$

(1)

5. Repeat steps (2)-(4) until the difference of $G$ is smaller than $\Delta G$, which is a pre-set value. $G$ is the desired threshold.
6. After obtaining the threshold, each pixel of the source image $f(x, y)$ is evaluated according to the formula (2), and the image is transformed to binary. The segmentation results are shown in Figure 2 (c).

$$g(x, y) = \begin{cases} 
0 & f(x, y) \geq G \\
255 & f(x, y) < G 
\end{cases}$$

(2)

2.3 Accurate contour Extraction based on multi contour tracking

Boundary describe the target object in images (Rödig G, Prasser C, Keyl C, 1999). It contains a wealth of information, such as direction, shape, and so on. It is an important method of image feature extraction in image recognition.

Boundary from binary images can be extracted by digging out the internal pixels. If 8 adjacent pixels of a white pixel are all white pixels, then this pixel is an internal point. On the contrary, it can be judged as the contour pixel. All internal pixels are set as background to complete the boundary extraction. The task can be accomplished by simply judging whether the values of 8 neighbors are same as $P$. If the answer is “YES”, then it is an internal point, otherwise it is a boundary point. As shown in figure 3.
Contour tracking is to obtain the boundary sequence based on boundary pixels. That is to say, the contour points will be stored in the stack in a certain order by tracking algorithm. As mentioned above, multiple objects are extracted from background because of the food or excrement of rodent in the experiment. In addition to extracting chain code of contour, it is necessary to solve the problem of labeling multi contour region and extraction maximum contour. The solution of this study is to add the region mark in the contour tracking algorithm. The algorithm is shown in Figure 4, the steps are as follows.

1 According to the order from bottom to top and from left to right, the first point is on bottom left of the boundary, denote it as A0. Store the sequence number, coordinate values and the chain code value of the current pixel in tree structure for the subsequent feature extraction. At the same time, add an integer tag to this point from 1.

2 Start from A0. Defines the initial search direction along the upper left;

3 If the pixel on top left is black, it is the boundary point. Otherwise search pixel with rotation 45 degrees clockwise, find the first black point, marked as A1. Store the sequence number, coordinate values and the chain code value of A1. The tag value of A1 is same as that of A0.

4 Continue to search the next black point in the same way, marked as A2.

5 If An is equal to A1, which is the second boundary point, and An-1 is equal to the first boundary point A0, stop searching and tracking, otherwise continue them by repeating step 2 - 4.

6 The sequence A0, A1, A2, ..., An-2 is the result of tracked contour.

7 If there are unmarked points (tag value is empty), indicating that it is the boundary of another region, continue from step 1. The value of tag increased by 1.

8. Continue with step 1-6 from the new point until all points are marked.
2.4 Features extraction of body and tail

The tail length parameter cannot be directly replaced by the number of columns of the segmented tail, because of the tail is curve sometimes. The calculation method of this paper is based on the contour image, calculate the pixels counts in the chain list of the tail contour. Set the summary as $T_a$, the tail length $T_l$ is calculated by formula (3).

$$T_l = T_a/2 \quad (3)$$

Map the segmentation point of tail and body to the contour image. The body part of the contour image can be obtained. Based on this, the long axis and short axis of the body can be calculated. The basic idea is to find the minimum bounding rectangle of body contour. Draw two perpendicular lines at the center point of the rectangle, and intersect with contour to produce two line segments. They are the long axis and short axis of rodent body. The algorithm details are as follows.

Step1: Take chain code contour as input parameters of function minAreaRect in OpenCV library, it returns a RotatedRect object, set the object as R.

Step2: Get center, size and angle of R object, the data types are Point2f, Size2f and float, respectively. They represent the center of the rectangle, width and height of the rectangle and the rotation angle.

Step3: Set an array with data type Point2f, namely vertices [4], obtain the four points of the rectangle by R.points (vertices). They are stored in 4 arrays, namely $A(x_a,y_a)$, $B(x_b,y_b)$, $C(x_c,y_c)$, $D(x_d,y_d)$. As shown in Figure 5. The coordinates of E, F, G, H, M, N, I and K can be calculated based on existing information. The distance between MN and IK can also be calculated.

![Figure 5](image)

Figure 5 The smallest envelope rectangle and the axis of the rodent

3. Results and analysis

4 common species of rodents in Southwest of China were selected as materials to verify the validity of this method, which are Apodemus agrarius, Microtus Fortis, Rattus norvegicus and Mus musculus respectively. The results are show as Table 1.

| Shape Features     | Apodemus agrarius | Microtus fortis | Rattus norvegicus | Mus musculus |
|--------------------|-------------------|-----------------|-------------------|--------------|
| Length of tail (mm)| 65.5              | 52.2            | 112.1             | 61.5         |
| Long axis of body (mm) | 72.7              | 112.56          | 179.36            | 77.49        |
| Short axis of body (mm) | 38.2              | 56.0            | 97.47             | 42.81        |
| Ratio of body and tail | 1.10              | 2.15            | 1.6               | 1.26         |
| Ratio of long axis and short axis | 1.90              | 2.01            | 1.84              | 1.81         |
As can be seen from table 1, the standard deviation of body area of Rattus norvegicus is maximum. This is due to the relatively body size of Rattus norvegicus is larger than other rodent species. For different ages of this species, physical development has a greater difference. In the process of image data acquisition, the activity of rodents will cause the measurement error. The data of tail length, long axis of body, short axis of body, ratio of body and tail show that the measured data are consistent with the actual data.

4. Conclusion
This paper presents a scheme for automatic recognition of rodent species by machine vision. They have strong representation of the shape features.

The global threshold method is suitable for segmenting rodent image from background. Chain code analysis method is used to track the contour. Multi-contour tracking extraction method is used to remove the non-rodent region. Tail length, body length, body height, the proportions of tail and body are extract based on contour analysis. The combination of these methods can extract the visual features of rodents effectively.

The experimental scheme can collect multiple data sets in different space real time. It can save manpower and material resources, improve work efficiency. At the same time, it can avoid the subjective error and the disturbance to the experimental animals. It can provide basic data for analyzing the life habits and population evolution of field rodents.

Acknowledgements
This paper is sponsored by National Science and technology support program of China(2012BAD19B02); and Science and technology program of Chongqing Education Commission (KJQN201800536). The intellectual property rights related to the experimental materials and the experimental results belong to Mr. Liliang Han.

References
[1] Ayelet A B, Hagit D, Yoseph A. (2016). Multimodal Correlative Preclinical Whole Body Imaging and Segmentation. Scientific Reports. 6:27940.
[2] Bakir G, Hofmann T, Schölkopf B. (2007). Support Vector Machine Learning for Interdependent and Structured Output Spaces. Predicting Structured Data. MIT Press.85-103.
[3] Chang C Y, Chang C W, Kathiravan S. (2016). DAG-SVM based infant cry classification system using sequential forward floating feature selection. Multidimensional Systems & Signal Processing.1-16.
[4] Giancardo, L., Sona, D., Huang, H., Sannino, S., Managò, F., & Scheggia, D., et al. (2013). Automatic visual tracking and social behaviour analysis with multiple mice. Plos One, 8(9), e74557.
[5] Hao S, Hu J, Liu S. (2015). Network traffic classification based on improved DAG-SVM International Conference on Communications, Management and Telecommunications.256-261.
[6] Huang Z L, Zheng J, Wen-Xin H U. (2013). Text classification based on inter-class separability DAG-SVM. Journal of East China Normal University.53 (3), 209-218.
[7] Millasseau S C, Kelly R P, Ritter J M. (2002). Determination of age-related increases in large artery stiffness by digital pulse contour analysis. Clinical Science. 103(4):371.
[8] Millasseau S C, Ritter J M, Takazawa K. (2006). Contour analysis of the photoplethysmographic pulse measured at the finger. Journal of Hypertension. 24(8):1449.
[9] Rousseau J B I, Lochem P B A V, et al. (2000). Classification of rat behavior with an image-processing method and a neural network [J]. Behavior Research Methods, 32(1):63-71.
[10] Rödig G, Prasser C, Keyl C. (1999). Continuous cardiac output measurement: pulse contour analysis vs thermodilution technique in cardiac surgical patients. British Journal of Anaesthesia. 82(4):525.
[11] Schomaker L, Bulacu M. (2004). Automatic writer identification using connected-component contours and edge-based features of uppercase Western script. IEEE Transactions on Pattern Analysis & Machine Intelligence. 26(6):787.

[12] Xun Y, Chen X, Li W. (2007). Automatic recognition of on-tree apples based on contour curvature. Jiangsu Daxue Xuebao, 28(6), 461-464.

[13] Yi H, Song X, Jiang B. (2011). Structure selection for DAG-SVM based on misclassification cost minimization. International Journal of Innovative Computing Information & Control Ijicic.7 (9), 5133-5143.

[14] Zhang C, Zhao-Feng M A, Niu X X. (2012). A Method Based on Dynamic Sequence Analysis of an API and DAG-SVM Multi-class Support Vector Machines of Unknown Virus Detection. Journal of Chinese Computer Systems.33 (12), 2724-2728.

[15] Zhang M, Zhang H Y, Zheng X X. (2006). Automatic recognition of rat's postures based on contour curvature and hierarchical clustering analysis. Journal of Zhejiang University. 40(3), 524-481.