Behavior Classification and Image Processing for Biorobot-rat Interaction

Zirong Wang
School of Electric and Engineering, Harbin University of Science and Technology, Harbin 150080,China
Wangzirong8@126.com

Hong Qiao
Complex System and Intelligence Science, Institute of Automation, China Academy of Sciences, Beijing 100190, China
hong.qiao@ia.ac.cn

Abstract—**In this paper, we focus on rat's behavior classification for biorobot-rat interaction. The automatic behavior analysis and classification of laboratory rats can effectively improve the adaptivity of interaction between rat-like robot and biological rats. Basic image processing algorithm as Labeling and Contour Finding were employed to extract feature parameters (body length, body area, body radius, rotational angle, and ellipticity) of rat's actions. These feature parameters are integrated as the input feature vector of CNN (Convolutional Neural Network) and SVM (Support Vector Machine) training system respectively. Preliminary experiment result shows that the grooming, rotating, crouching and rearing actions could be recognized with extremely high rate (more than 90%) by both CNN and SVM. Furthermore, CNN provides better recognition rate and SVM provides less computational cost.**

Keywords: behavior classification; image processing; CNN; SVM;

I. INTRODUCTION

The study of rat's behavior had a long history covering many fields, and has significantly influenced progress in neuroscience, psychology, pharmacology, and brain science. In the study of rat's behavior, social behavior has drawn much attention for completely different reasons. Social behavior refers to the actions that affect other conspecifics presently or in the future and is an indicator of anxiety levels and sociality. The anxiety levels and sociality of rat models should be evaluated via behavioral tests such as social interaction test, which is regarded as one of the main indices of human mental disorder symptoms [1]. Generally, rats or mice are used for such models due to their genetic consistency and the similarity with human beings in drug reaction. The rat models of mental disorder (RMMD) are created by genetic manipulation, surgical operation on the brain, psychotropic drugs or stressful environment [2]. Therefore, it is of great significance to study the classification of rat's behavior in the treatment of mental disorder and screening of psychotropic drugs in the field of psychology and pharmacology.

However, the rat's behavior classification work are mainly performed visually by Experienced biologists, yielding significant classification errors due to individual differences. In addition, the classification of rat's behaviors is time consuming and not readily compatible with experiments requiring large groups of rats. Therefore an automated behavior recognition and behavior classification system will contribute a lot for solving such problems. In the interaction experiment between the robot rat and the biological rat, the automatic analysis and classification of the biological rat behavior will obviously improve the experimental efficiency and effect.

II. RELATED WORK

In an attempt to develop an automated behavior recognition system. Twining et al [3] designed an automated image analysis system by using irregular models of shape (active shape models) to interpret video images of rodents. This method can distinguish various behaviors of rats with good accuracy. But, significantly high computational cost makes it impossible to perform real-time recognition. In [4], a quite effective framework for automatic video based behavior analysis systems for rats was proposed. It achieved high recognition rate of resting, eating, exploring and grooming. However, since the behaviors were obtained manually in the squirrel cage, it can not accurately and practically represent the real behaviors of rats. Nie et al. [5] proposed an automated behavior recognition algorithm for laboratory rat. The effectiveness of this system is evaluated for six typical behaviors, such as scratching and grooming. This algorithm performs very well though, its research purpose and application is different with our project. In addition, wireless inertial sensors have been developed for monitoring small animal behavior as well. As introduced in [6], a small wireless accelerometer that is able to record and monitor the activity of rats over time. However, the behavior of rats tends to be easily influenced by the body-worn sensors, so the behavior of rats is not exhibited naturally.

Due to the above mentioned shortcomings, we are aiming to propose a novel automated recognition system to measure rat behavior in real-time based on straightforward image processing and classification methods. Furthermore, it should be able to distinguish the behavior of rats in real-time to ensure that the robot to interact with rats in a natural way, and therefore makes a step towards realistic application.

III. IMAGE PROCESSING AND FEATURE EXTRACTION

For now, we are focusing on the typical actions of rats, such as moving, rearing, grooming, rotating, crouching etc, which is significantly important for behavior analysis of rats. As for moving, we can regard it as the locomotion speed of centroid. The definition of other actions can be concluded as, Rearing: rise up on hind limbs; Grooming: body cuddles and

978-1-5090-3025-5/17/$31.00 ©2017 IEEE

head curls; Rotating: body bends during moving; Crouching: body curled up and tail stretched.

Given the image of rat's behaviors, the crucial geometric features for representing rat behavior is extracted as shown in Fig.1. Specifically, body length L, body area S, body radius R, circularity E, rotational angle θ, ellipticity ρ and tail Length l are extracted as the static feature parameters. Locomotion speed of centroid (V_{cx}, V_{cy}), tail root (V_{trx}, V_{try}), tail tip (V_{ttx}, V_{tty}), nose point (V_{nx}, V_{ny}), their angular speed of rotation ω could be calculated respectively, which were considered as dynamic parameters. So the feature vector is an 16*1 vector:

$$X = [L, S, R, E, \theta, \rho, l, V_{cx}, V_{cy}, V_{trx}, V_{try}, V_{ttx}, V_{tty}, V_{nx}, V_{ny}, \omega]^T$$

Firstly it is essentially to extract the clue points: centroid, tail root, tail tip, nose point.

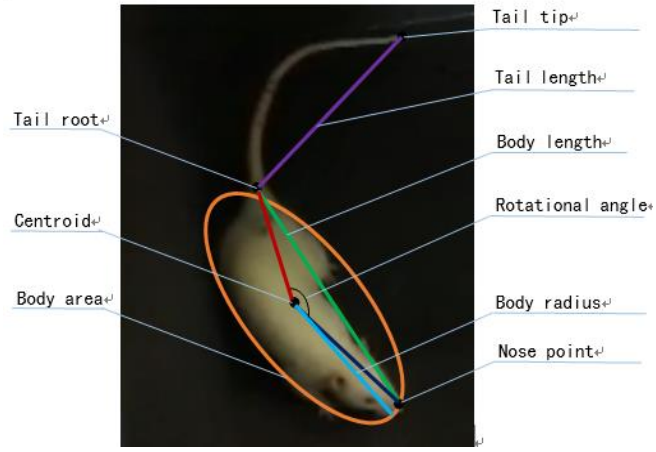

Figure 1. Crucial geometric features to distinguish rat behavior

A. Clue Points

The centroid, tail root, tail tip and nose point of the rat are extracted based on the following image processing algorithm. Given the source input gray image sequence $I(x, y, t)$, the threshold image sequence $Th(x, y, t)$ can be calculated based on the threshold gray value T_b as described in (1). After implementing erosion to eliminate noise, the body image I_E (white region) of the rat is obtained.

$$Th(x, y, t) = \begin{cases} 255 & \mathrm{I}(x, y, t) > T_b \\ 0 & \text{其他} \end{cases} \tag{1}$$

Definitely,the largest white region is considered to be the rat body evidently. Here, we employ the labeling algorithm[7] to extract the largest region. After obtaining the rat body, we can get all the pixel coordinates of it, so the centroid of it can be calculated as the following equations.

$$(c_x(t), c_y(t)) = (\frac{M_x(t)}{S(t)}, \frac{M_y(t)}{S(t)}) \tag{2}$$

$$S(t) = \sum_{x,y} D(x, y, t) \tag{3}$$

$$M_x(t) = \sum_{x,y} xD(x, y, t) \quad M_y(t) = \sum_{x,y} yD(x, y, t) \tag{4}$$

Here, $(c_x(t), c_y(t))$ is the coordinate of centroid, $D(x, y, t)$ is the binarized image of $Th(x, y, t)$, $S(t)$ is the area of rat body in number of pixels.

We assume the tail root $(t_{rx}(t), t_{ry}(t))$ in the body contour $b(x, y, t)$ is determined by calculating the minimum distance between the tail and centroid. The tail tip $(t_{tx}(t), t_{ty}(t))$ is determined by calculating the maximum distance between the tail and tail root. The nose point $(n_x(t), n_y(t))$ in the body contour $b(x, y, t)$ located in the maximum distance between centroid and body contour.These three points is determined by the following three equations respectively. f is a function to calculate the distance.

$$(t_{rx}(t), t_{ry}(t)) = \arg\min_{x,y} f(b(x, y, t), (c_x(t), c_y(t))) \tag{5}$$

$$(t_{tx}(t), t_{ty}(t)) = \arg\max_{x,y} f(t(x, y, t), (t_{rx}(t), t_{ry}(t))) \tag{6}$$

$$(n_x(t), n_y(t)) = \arg\max_{x,y} f(b(x, y, t), (c_x(t), c_y(t))) \tag{7}$$

B. Calculate Feature Parameters

Given (2), (5) , (6) and (7), the speed of centroid, tail root, tail tip and nose point can be calculated by the following equations respectively.

$$V_{cx} = \frac{\partial c_x(t)}{\partial t} \quad V_{cy} = \frac{\partial c_y(t)}{\partial t} \tag{8}$$

$$V_{trx} = \frac{\partial t_{rx}(t)}{\partial t} \quad V_{try} = \frac{\partial t_{ry}(t)}{\partial t} \tag{9}$$

$$V_{ttx} = \frac{\partial t_{tx}(t)}{\partial t} \quad V_{tty} = \frac{\partial t_{ty}(t)}{\partial t} \tag{10}$$

$$V_{nx} = \frac{\partial n_x(t)}{\partial t} \quad V_{ny} = \frac{\partial n_y(t)}{\partial t} \tag{11}$$

Evidently, Body length L is the distance between tail root and nose point. Tail length l is the distance between tail root and tail tip.Body radius R is the maximum distance between centroid $(c_x(t), c_y(t))$ and ellipticity contour.The circularity E is the square proportion relationship between S and R. Once supposing the centroid, tail root and nose point as the vertices of a triangle, body bend angle θ (an internal angle of the triangle formed by the three points) can be computed. The angular speed of rotation ω is obtained by differentiating θ with respect to time.

$$d_{(0,2)}(t) = \sqrt{(c_x(t) - t_{rx}(t))^2 + (c_y(t) - t_{ry}(t))^2} \tag{12}$$

$$d_{(0,1)}(t) = \sqrt{(c_x(t) - n_x(t))^2 + (c_y(t) - n_y(t))^2} \tag{13}$$

$$d_{(1,2)}(t)=\sqrt{(n_x(t)-t_{rx}(t))^2+(n_y(t)-t_{ry}(t))^2} \quad (14)$$

$$\theta(t)=\arccos\frac{d_{(0,1)}^2(t)+d_{(0,2)}^2(t)-d_{(1,2)}^2(t)}{2d_{(0,1)}(t)d_{(0,2)}(t)} \quad (15)$$

$$\omega(t)=\frac{\partial\theta(t)}{\partial t} \quad (16)$$

In general, the body shape of rats appears long and narrow during most of its behavors. According to the appearance of the body and the body contour $b(x,y,t)$, we can fit appropriate ellipse to the rat's body. Through the long and short axis $(e_a(t),e_b(t))$ of the fitted ellipse, the ellipticity ρ is computed as the following equation.

$$\rho(t)=\frac{e_a(t)}{e_b(t)} \quad (17)$$

IV. CLASSIFICATION OF RAT BEHAVIOR

A. Classification Methods

After obtaining the feature parameters, the powerful and straightforward CNN[8] and SVM[9] classification methods are adopted to classify rat behavior.

The structure of CNN includes input layer, convolution layer, max-pooling layer, full connected layer, and output layer. Each layer has multiple feature maps, every one of which also has multiple neurons. Each feature map extracts one feature of input layer by using one convolution filter. Convolution layer and max-pooling layer are the core modules of the feature extraction in the CNN. The parameters of the network weights are adjusted through the gradient descent method by minimizing the cost function[10]. and the network accuracy is gradually approached through repeatedly iteration process.

A 6-layer CNN is designed in this paper, which applies to one-dimensional rat's behaviors classification. The network structure is based on that of LeNet-5 (the structure of Lecun handwriting recognition CNN [11]) and the DCNN in [12]. The proposed structure of the 6-layer CNN is shown in Fig 2.

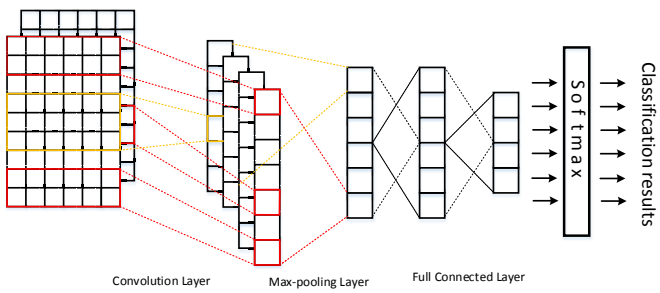

Figure 2. Architecture of a 6-layer convolutional neural network

An SVM performs classification by constructing an N-dimensional hyperplane that optimally separates the input vectors into two categories. To make the separation easier to perform, the concept of kernel function is introduced to make the input vectors into a higher dimensional space. In this way, a linear separation in the new space becomes equivalent to a non-linear classification in the original space. In this research, a nonlinear classifier with a RBF (Radial Basis Function) kernel $K(x,x_i)=e^{-\gamma|x-x_i|^2}$ is used according to the advantages narrated in LIBSVM[13]. Besides γ, another parameter is C (the penalty parameter of the error term) [14] . gives an effective method about how to determine the best parameter C and γ, here 2 and 0.07 are chosen respectively.

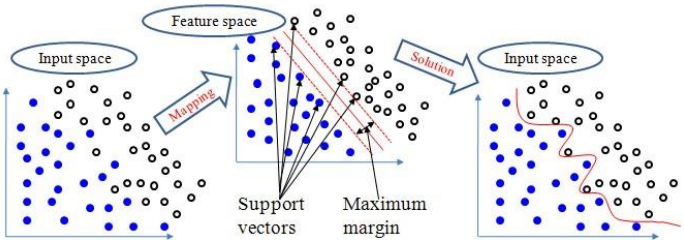

Figure 3. Overview of the Support Vector Machine process. Transform input vectors into a higher dimensional space to make it possible to perform the separation. As in general, separation becomes easier in higher dimension.

B. Data Acquisition and Training

Video streams in approximately 30 f/s of the object rat aged 9 weeks were captured. The record time of the object rat is 30 min. Consequently, the number of total frames is 30min * 60sec/min*30f/sec =54000f. We extract those feature parameters in each rame. All the feature parameters are packaged as the input dataset of the CNN and SVM.

With regard to recognizing rat's actions, we have employed the CNN and SVM training method to train dataset respectively. Here, we divided all the dataset (54000 patterns) into two parts: 49600 training set (90% of the whole dataset) and 5400 validation set (10% of the whole dataset).

Regarding CNN, after each training pattern is trained, we can get a trained result, if the trained result is equal to the correct truth, the number of correct result will increase. When the entire training set is covered, an epoch is completed. The errors between the desired and actual outputs are computed at the end of each iteration and these errors are averaged at the end of each epoch. The training process is terminated when specified maximum number of epochs (1000) is exceeded or error rate is less than 1%. We can get the training rate by calculating the ratio between the number of correct trained results and total trained patterns. During training process, we updated the trained weights to decease the errors. Furthermore, we use the finally updated weights to evaluate validation patterns. Similarly we can get validation rate by calculating the ratio between the number of correct validated results and total validation patterns. Regarding SVM, we use the best parameter C(2) and γ(0.07) of the RBF kernel function to model the dataset. This SVM model then serves to calculate the recognition rates of training and validation set respectively.

C. Classification Results

Table.I illustrates the classification results.All The recognition rate of the validation set is close to the recognition rate of the training set, which fully states the effectiveness of CNN and SVM. The four actions can be classified with rates of

over 90% by both CNN and SVM, proving the robustness of this recognition methods. However, the recognition rates of CNN are higher than that of SVM as a whole. That is because CNN can fully extract and use feature vectors for image classification. Assuredly,the SVM can also find an optimal classification hyperplane by support vectors based on the RBF kernel function. Table.II shows the mean execution time of recognition training process with respect to SVM and CNN respectively. The system based on common PC framework, using Intel Core i7 3.6G CPU, 4G RAM. Execution time of SVM is ~7 times lower than that of CNN, which shows the optimization of SVM training system. In addition, the execution time of grooming and crouching recognition is less than rearing and rotating recognition in SVM, approving the easier classification of grooming and crouching than others.

TABLE I
RESULTS OF BEHAVIOR CLASSIFICATION

	Recognition rate(%)			
	SVM		CNN	
Behavior	Training	Validation	Training	Validation
Rearing	92.0±0.15	92.06±0.11	94.5±0.27	93.2±0.29
Grooming	98.8±0.02	98.3±0.03	99.0±0.04	99.6±0.09
Rotating	91.1±0.10	91.2±0.16	94.5±0.17	93.6±0.23
Crouching	97.1±0.04	97.2±0.06	98.5±0.17	98.6±0.23

TABLE II
EXECUTION TIME OF TRAINING

Action	Feature space	Mean execution time(s)	
		SVM	CNN
Grooming	L-S-R-ρ	0.559	15.766
Rearing	S-R-θ-ρ	2.448	15.734
Rotating	θ-ρ	1.7	14.235
Crouching	L-S-R-ρ	0.559	14.815

V. CONCLUSIONS AND FUTURE WORK

This paper proposed an automated behavior recognition and behavior classification system to improve the adaptivity of the rat-like robot to interact with rats. The main contribution of this paper lies in the real-time recognition of rat behavior and the classification of their behavior.

We employed basic image processing algorithm to extract feature parameters (body length, body area, body radius, circularity, rotational angle, tail length, and ellipticity) of rat behavior. Through these static parameters, we can calculate the dynamic feature parameters such as locomotion speed of centroid, tail root, tail tip, nose point, and angular speed of rotation. These parameters are integrated as the input feature vector of CNN and SVM classification methods respectively. Experiments show that the rearing, grooming, rotating and crouching actions could be recognized with extremely high rate. Furthermore, the recognition rates of CNN are higher than that of SVM as a whole . However, SVM needs less training computational cost than CNN. Therefore, taking the overall classification and real-time requirements into account. SVM is more suitable as the classification methods for the behavior recognition of rats.

For the further work, on one hand ,We will improve this rats behavior classification system based on RGB color backgrounds to enhance the ability of rodent behavior recognition and classification. On the other hand, we will conduct social interaction experiment between a robot and rats based on this antomated classifition system.

ACKNOWLEDGMENT

This project was supported by National Science and Technology Major Project.and Key Laboratory of Complex System and Intelligence Science, Institute of Automation, China Academy of Sciences.

REFERENCES

[1] S.E. File, and P. Seth, "A review of 25 years of the social interaction test," *European Journal of Pharmacology*, Vol. 463(1-3), pp. 35-53, 2003.

[2] A.M. Gardier, B.P. Guiard, J.P. Guilloux, C. Repe´rant, F. Coudore´, and D.J. David,"Interest of using genetically manipulated mice as models of depression to evaluate antidepressant drugs activity: a review," Fundamental and Clinical Pharmacology, Vol. 23(1), pp. 23-42, 2009.

[3] C.J. Twining, C.J. Taylor, and V. Rabaud, "Robust tracking and posture description for laboratory rodents using active shape models,"Behavior Research Methods, Instruments and Computers, Vol. 33(3), pp. 381- 391, 2001.

[4] X. Xue, and T. C. Henderson, "Feature fusion for basic behavior unit segmentation from video sequences," Robotics and Autonomous Systems 57, pp. 1595-1600, 2011.

[5] Y. Nie, T. Tkaki, I. Ishii, and H. Matsuda, "Behavior Recognition in Laboratory Mice Using HFR Video Analysis," in 2011 IEEE Int. Conference on Robotics and Automation, pp. 239-248, 2009.

[6] G. Eason, B. Noble, and I. N. Sneddon, "On certain integrals of Lipschitz-Hankel type involving products of Bessel functions," Phil. Trans. Roy. Soc. London, vol. A247, pp. 529–551, April 1955. (references).

[7] http://chihara.naist.jp/people/STAFF/imura/products/labeling

[8] Geng C, Song J X. Human Action Recognition based on Convolutional Neural Networks with a Convolutional Auto-Encoder[C]// International Conference on Computer Sciences and Automation Engineering. Atlantis Press, 2016.

[9] N. Cristianini, and J. Shawe-Taylor, "An Introduction to Support VectorMachines and Other Kernel-Based Learning Methods," Cambridge University Press, 2000.

[10] Guyon I, Albrecht P, Cun Y L, et al, "Design of a neural network character recognizer for a touch terminal," Pattern Recognition, 1991, 24(2):105-119.

[11] Lécun Y, Bottou L, Bengio Y, et al, "Gradient-based learning applied to document recognition," Proceedings of the IEEE, 1998, 86(11):2278-2324.

[12] Hu X, Zhu H, Xu J, et al, "Wrist pulse signals analysis based on Deep Convolutional Neural Networks," Computational Intelligence in Bioinformatics and Computational Biology, 2014 IEEE Conference on. IEEE, 2014:1-7.

[13] C.C. Chang, and C.J. Lin, "LIBSVM: a library for sup- port vector machines," 2001. Related software available at http://www.csie.ntu.edu.tw/ cjlin/libsvm

[14] C.W. Hsu, C.C. Chang, and C.J. Lin,"A Practical Guide to Support Vector Classification", 2010. Available website at http://www.csie.ntu.edu.tw/ cjlin/papers/guide/guide.pdf