34th Annual International Conference of the IEEE EMBS
San Diego, California USA, 28 August - 1 September, 2012

Motion States Extraction with Optical Flow for Rat-robot Automatic Navigation*

Xinlu Zhang[1] Chao Sun[2] Nenggan Zheng[3] Weidong Chen[4] and Xiaoxiang Zheng[5]

***Abstract*— The real-time acquisition of precise motion states is significant and difficult for bio-robot automatic navigation. In this paper, we propose a real-time video-tracking algorithm to extract motion states of rat-robots in complex environment using optical flow. The rat-robot's motion states, including location, speed and motion trend, are acquired accurately in real time. Compared with the traditional methods based on single frame image, our algorithm using consecutive frames provides more exact and rich motion information for the automatic navigation of bio-robots. The video of the manual navigation experiments on rat-robots in eight-arm maze is applied to test this algorithm. The average computation time is 25.76 *ms* which is less than the speed of image acquisition. The results show that our method could extract the motion states with good performance of accuracy and time consumption.**

I. INTRODUCTION

Brain computer interface (BCI) which builds a direct interaction between the animal's brain and computers provides an approach to implement a new type of robot system, bio-robots. Since 1990s, a variety of bio-robots have been developed, including insects [1], geckos [2], sharks [3-4], pigeons [5] and rats [6-8]. Micro-electrodes are implanted in specific areas of the animal's brain. Through mild electrical stimulation, some 'virtual' feelings can be generated, such as rewards, punishment, and somatosensory cues. With these stimulations as controlling commands, human operators can induce animals to perform complex tasks as well as robot systems.

The development of bio-robot has made remarkable progress. However, the current bio-robots have been largely restricted in practical applications due to the dependency on guidance from human operators. In rescue or exploration missions in which the real-time supervision and human guidance is not available, bio-robots should be controlled automatically. Meanwhile in certain behavioral or psychological experiments such as the evaluation and modeling of animals' behavioral reactions to electrical stimulation, human inference needs to be excluded because of its uncertainty and haphazardry.

*This work was supported by grants from the National Natural Science Foundation of China (No. 61031002, 61003150), Zhejiang Provincial Key Science and Technology Program for International Cooperation(No. 2011C14005), the Fundamental Research Funds for the Central Universities

[1]Xinlu Zhang, [2]Chao Sun, [3]Nenggan Zheng,[4]Weidong Chen and [5]Xiaoxiang Zheng are with Qiushi Academy for Advanced Studies (QAAS), Zhejiang University, Hangzhou 310027, China. [3]Nenggan Zheng is the corresponding author (email: qaas@zju.edu.cn).

[5]Xiaoxiang Zheng is also with the Department of Biomedical Engineering, Zhejiang University, Hangzhou 310027, China. [1]Xinlu Zhang and [2]Chao Sun are also with the College of Computer Science, Zhejiang University, Hangzhou 310027, China.

The automatic navigation for bio-robots remains an essential challenge. It is mainly due to the navigation systems cannot provide motion states of bio-robots accurately and automatically in real time. Comparing traditional mechanical robots, the body of bio-robot is non-rigid and multi-variant, which makes the motion states hard to be extracted. For automatic navigation the motion states extraction should meet two requirements. Firstly, the states must provide enough and precise motion information that supports controlling decision making. Secondly, the extracting algorithm calculates with low time cost which ensures the motion information are extracted in real time.

Although the automated video tracking for animals has been studied during last two decades, the tracking methods couldn't be applied in automatic navigation of bio-robots subject to the requirement mentioned above. For rodents, many systems are mainly developed for the investigation of the effects of drugs, novel therapeutic interventions or genetic mutations on behavior [9-10]. In these studies, researchers mostly focus on the position of the rat in restrictive environment such as [9] [11], which are not enough for the controlling decision making of bio-robot. In [12], the video tracking system developed to recognize rodent behavioral activities could only classify three simple behaviors (sitting, rearing and walking). Extraction algorithms in navigation should take time consumption into consideration, which the mentioned pharmacology studies neglected. In [13] an automatic control system for rat-robot navigation with image processing and infinite state machine techniques has been proposed. The motion states extraction in this system performs well in the simple experimental scenes. However, this algorithm suffers from the complexity in real-world environment, and needs a external marker which not belong to the rat-robot system to determine the motion states. Furthermore, the rat-robot's motion direction is computed with single frame image and defined as orientation in given time, ignoring the motion trend and intention of the animal.

In this paper, we proposed a video tracking algorithm to extract the motion states of rat-robot, including location, speed and motion trend. Optical flow is used to track and provide the necessary information to calculate these states. The test with navigation video shows that our algorithm provides multiple motion states accurately. Meanwhile the analysis of the calculation time indicates the extraction could be used in automatic navigation in real time.

The remainder of this paper is organized as follows. In session II, we describe the rat-robot navigation and the optical flow method used to track rat-robots. The results will

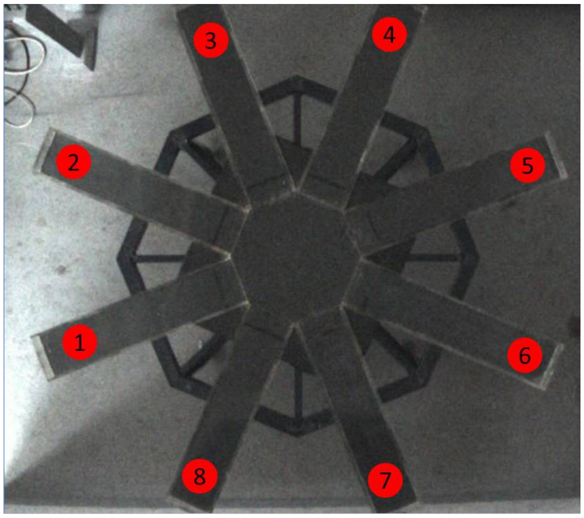


Fig. 1. The experiment environment of manual navigation

be introduced and discussed in session III. Finally, session IV will be the conclusion and our future plan.

II. METHODS

A. Rat-robot Navigation

The navigation experiments are performed with rat-robots of adult Sprague Dawley rats (230∼340 *g*). Stimulating electrodes were made from pairs of insulated nichrome wires (80 μm in diameter, California Fine wire Inc., USA) with a 0.5∼1 *mm* vertical tip separation. Two of the bipolar stimulating electrodes were placed in the MFB (AP-3.8, ML±1.6,DV+8.2) to generate excitement feelings as the command **FORWARD**. The other two stimulating electrodes were implanted symmetrically in the whisker barrel fields of left and right somatosensory cortices (SI) (AP-1.8, ML±5.0, DV+2.8) to function as the commands **LEFT** and **RIGHT**. A backpack was put on the back of rat to receive remote controlling instructions by bluetooth and transfer the instructions into electrical pulse to the brain. More details can be found in [7].

The video data used in this paper are captured from manual navigation experiments. The experimental scene is shown in Fig. 1. The whole experiment process is captured by a bird-eye camera. The rat-robot is steered to walk through each arm along the order of the numbers shown in the picture. The point 1 is the start point and the experiment ends when the rat-robot reach the point 8. Before the experiments, a background image without the rat-robot in the eight-arm maze is captured to calculate the approximate location. The supervisory video parameters are as follows: the resolution is 640×480, the video frame rate is 15 *fps* (frames per second).

B. Optical Flow

Optical flow estimation is one of the fundamental problems in computer vision. It refers to computing the motion of pixels between consecutive image frames. A full review of optical flow algorithms is beyond the scope of this paper. Interested readers are referred to previous surveys by Aggarwal and Nandhakumar [14], Barron et al. [15], Otte and Nagel [16], Mitiche and Bouthemy [17], and Stiller and Konrad [18]. Here we briefly introduce the basic principles of the optical flow.

As mentioned in [19], Once the inter-frame displacement is small enough, the assumption of intensity constancy can be assured. Let $I(x, y, t)$ denotes the image intensity at the time t whose spatial location is (x, y), we can have:

$$I(x,y,t) = I(x+\Delta x, y+\Delta y, t+\Delta t) \tag{1}$$

It means one pixel(x+Δx, y+Δy) in the current image at time t+Δt can be obtained by moving anther pixel (x, y) in the previous image taken at time t. The amount of motion $d = (\Delta x, \Delta y)$ is called the displacement of the point at $p = (x,y)$ in time Δt.

Because of the aperture problem, it is essential to define the notion of similarity in a 2D neighborhood sense. Let a and b two integers. We define the image velocity d as being the vector that minimizes the residual function ε defined as follows:

$$\varepsilon(d) = \sum_{X=x-a}^{x+a} \sum_{Y=y-b}^{y+b} (I(X,Y,t) - I(X+\Delta x, Y+\Delta y, t+\Delta t)) \tag{2}$$

Note that following the definition, the similarity function is measured on an image neighborhood of size $(2a+1)\times(2b+1)$. This neighborhood will be also called integration window. Here we choose a= b=10.

It's time consuming to calculate the optical flow information for the entire image. We just need to track the feature points located on the rat's body. To diminish the computational complexity and ensure compute the information in real time, background subtraction is taken first to obtain the approximate location of rat-robot, Fig. 2(a). After this operation, we adopt Shi-Tomasi corner detection algorithm [20] to select feature points which are on the rat-robot's body.

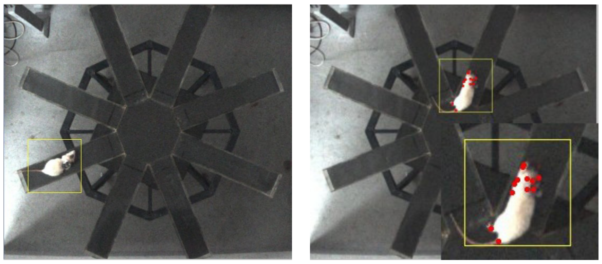
After get the approximate location of rat-robot (expressed as a rectangle), we compute the spatial gradient matrix G of each pixel within a small window around which is in the rectangle in the gray image. The spatial gradient matrix G is defined as follows:

$$G = \sum_{x=p_x-\omega_x}^{p_x+\omega_x} \sum_{y=p_y-\omega_y}^{p_y+\omega_y} \begin{bmatrix} I_x^2(x,y) & I_x(x,y)I_y(x,y) \\ I_x(x,y)I_y(x,y) & I_y^2(x,y) \end{bmatrix} \tag{3}$$

Observe that the image derivatives I_x and I_y may be computed directly from the gray image which represent the location of the rat-robot in the $(2\omega_x+1)\times(2\omega_y+1)$ neighborhood of the pixel (P_x, P_y). The two derivative images have the following expression:

$$\forall(x,y) \in [P_x-\omega_x, P_x+\omega_x] \times [P_y-\omega_y, P_y+\omega_y]$$

$$\begin{aligned} I_x(x,y) &= \frac{\partial I(x,y)}{\partial x} = \frac{I(x+1,y)-I(x-1,y)}{2} \\ I_y(x,y) &= \frac{\partial I(x,y)}{\partial y} = \frac{I(x,y+1)-I(x,y-1)}{2} \end{aligned} \tag{4}$$



(a) (b)

Fig. 2. (a)The approximate location of the rat-robot (the yellow rectangle) (b)The result of the feature points selection (the red points)

In order to ensure the pixels are 'easy to track', the minimum eigenvalue of G must be large enough. Therefore, the process of selection goes as follow:

- Call λ_{max} the maximum value of λ_m over the whole rectangle.
- Retain the image pixels that have a λ_m value larger than a percentage (10%) of λ_{max}.
- From those pixels, retain the local max. pixels (a pixel is kept if its λ_m value is larger than that of any other pixel in its 3×3 neighborhood).
- Keep the subset of those pixels so that the minimum distance between any pair of pixels is larger than a given threshold distance (5 pixels in our system).

Fig. 2(b) is the result of the feature point selection. Most of the feature points are on the articulation of the rat's body and the backpack. The pixels at those points have a mutation, so those points belong to 'easy to track'. The mean value of all feature points is defined as the location of the rat-robot. The position of the yellow rectangle will update according to the location of the rat-robot to track the rat-robot.

III. RESULTS

A video data of the manual navigation experiment is used to validate our algorithm. The speed, trajectory (which consists all location information) and motion trend can be calculated exactly. The low computational time cost of the algorithm ensures the practical application in the automatic navigation.

A. Speed and Trajectory

The speed and the trajectory of the rat-robot are shown in Fig. 3. As the experiment we mentioned above, the rat-robot is controlled by human operator to walk from point 1 to point 8. Besides 'the started arm' and 'the ended arm', the rat-robot walks along each arm twice. The yellow polyline demonstrates the trajectory of the rat-robot in this experiment. In our system, we calculate the speed every five frames. The red points in this picture represent the location where the rat-robot has a low speed (lower than 57 *pps*, pixel per second)while the green ones indicate the rat-robot is progressing with relatively higher speed at these locations. The threshold is the average speed of the whole experimental process. It is clear that the red points concentrate on the area where the rat made a turn, such as the end of each arm or the

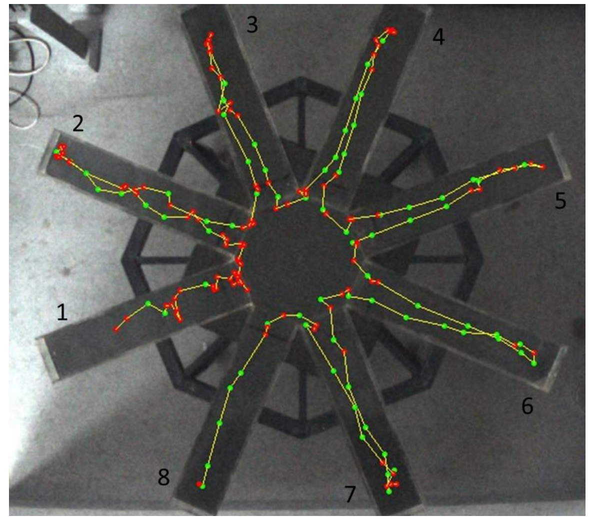


Fig. 3. The trajectory and the speed of the rat-robot. 1) The yellow polyline represents the trajectory. 2) The speed of the rat-robot is small in the red points, when it at the start or make a turn. The green points represent the high speed of the rat-robot when it is walking straight.

junction between arms. Most of green points are along the arms of the eight-arm maze. This is consistent with the actual situation, slow in the turn corner and fast in the straight line.

B. Motion Trend

In addition to the trajectory and the speed information, the motion trend of the bio-robot is also important for the automatic controlling. Compared to the traditional method based on single frame image [13], the optical flow algorithm based on consecutive frames can be more truly reflect the intention of the rat-robot. The direction computed in former work which is the instantaneous state at specified time cannot describe the motion trend of the rat-robot correctly. For example, the rat's orientation is toward the left at current moment, but the motion trend of the rat may be to the right. To demonstrate the motion direction computed in our algorithm, we choose 4 non-overlapping path segments of the experiment to shown in Fig. 4. The direction of the green arrow represents the motion trend of the rat-robot. The results show that the overall direction of motion of the arrows consistent with the trajectory of the rat-robot in our experiment.

C. Time Consumption

Unlike pharmacological studies, the experimental results must be figured out in real time for automatic navigation. In our system, the computation time of two frames varies from 15 *ms* to 47 *ms*. The average computation time is 25.76 *ms*. The proportion of computation time between frames is shown in TABLE I. More than 95 % of the computing time is less than 40 *ms*. The video frame rate in this paper is 15fps, with the time intervals between frames is about 66 *ms*. Thereby the computation time fits the speed of image acquisition.

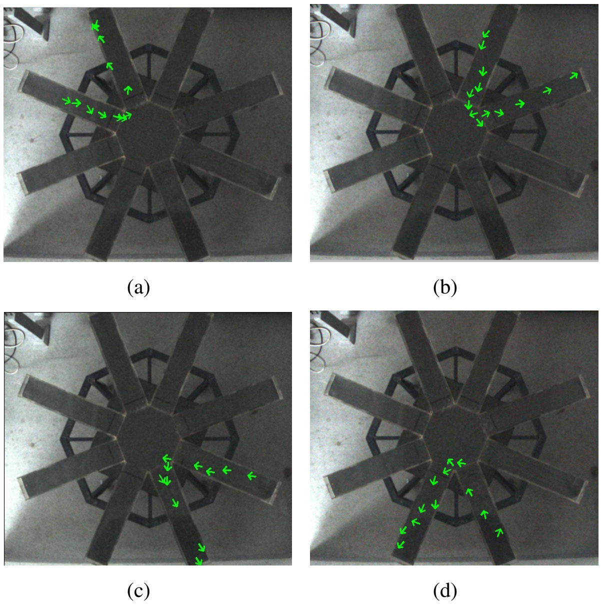


Fig. 4. The judgment of the motion trend of the rat-robot, each picture shows a part of the experiment, no overlap.

TABLE I
THE PROPORTION OF COMPUTATION TIME BETWEEN FRAMES

Computation Time between Frames	$\sim 20\ ms$	$20\ ms \sim 40\ ms$	$40\ ms \sim$
Proportion (%)	39.8	55.5	4.7

IV. CONCLUSION AND FUTURE WORK

A real-time extraction algorithm of the bio-robot's motion states based on optical flow tracking in complex environment was proposed. Using optical flow tracking, we obtained not only the location of the rat-robot, but also calculated the speed and motion trend information. The results showed that our method can track the rat-robot successfully and provide right direction of the motion trend of rat-robot. The computation time indicated that the algorithm could meet the requirement of real-time and be applied in automatic navigation of rat-robot without human inference.

This work aims to realize the automatic navigation for rat-robots. The reason to track the rat-robot and calculate its motion states is to provide the evidence for the generation of control instructions. Based on current results, some further work should be done. Firstly, the motion states information will be used in the automatic navigation system which is built on the state machine techniques to replace the old parameters. Secondly and mostly, the ultimate goal of motion states extraction is to implement the automatic navigation of rat -robot. The online experiments will be taken in the future.

ACKNOWLEDGMENT

The authors would thank Chaonan Yu, Fang Wang for the rats' surgery and helping training rats. Thanks also to Chen Zhang for taking care of rat-robot.

REFERENCES

[1] R. Holzer, and I. Shimoyama, Locomotion control of a bio-robotic system via electric stimulation, Proc IEEE/RSJ Inter Conf, vol. 3, pp. 1514-1519, 1997.
[2] Y. Wang, X. C. Su, and R. T. Huai, A telemetry navigation system for animal-robots, Robot, vol. 28, no. 2, pp. 183-186, 2006.
[3] W. Gomes, D, Perez, and J Catipovic, Autonomous shark tag with neural reading and stimulation capability for open-Ocean experiments, J Eos Transactions, vol. 87, pp. 36, 2006.
[4] S. Brown, Stealth sharks to patrol the high seas, New Scientist, pp. 30-31, 2006.
[5] Shandong University of Science and Technology, SDUST Created remote -controlled pigeon, World Wide Web electronic publication, 2007.
[6] S. K. Talwar, S. Xu, and E. S. Hawley, Rat navigation guided by remote control, J Nature, vol. 417, no. 6884, pp. 37-38, 2002.
[7] Z. Y. Feng, W. D. Chen, and X. S. Ye, A remote control training system for rat navigation in complicated environment, J Zhejiang Univ Sci A, vol. 8, no. 2, pp. 323-330, 2007.
[8] W. G. Song, J. Chai, and T. Z. Han, A remote controlled multimode micro-stimulator for freely moving animals, Acta Physiologica Sinica, vol. 58, no. 2, pp. 183-188, 2006.
[9] L. P. Noldus, A. J. Spink, and R. A. Tegelenbosch, EthoVision: a versatile video tracking system for automation of behavioral experiments. Behav Res Methods Instrum Comput, vol. 33, pp. 398-414, 2001.
[10] C. V. Vorhees, K. D. Acuff-Smith, and D. R. Minck, A method for measuring locomotor behavior in rodents: contrast-sensitive computer-controlled video tracking activity assessment in rats, Neurotoxicol Teratol, vol. 14, pp. 43-9, 1992.
[11] S. I. Dworkin, J. B. Zurn, and D. Hohmann, A real-time rodent tracking system for both light and dark cycle behavior analysis, in: Proceedings of the IEEE Workshop on Applications of Computer Vision, pp. 87-92, 2005.
[12] J. B. Zurn, X. Jiang, and Y. Motai, Video-based tracking and incremental learning applied to rodent behavioral activity under near-infrared illumination, IEEE Trans, Instrum. Meas. vol. 56, pp. 2804-2813, 2007.
[13] Y. M. Zhang, C. Sun, and N. G. Zheng, An Automatic Control System for Ratbot Navigation, 2010 IEEE/ACM Int'l Conference on Green Computing and Communications & Int'l Conference on Cyber, Dec 18-20, pp. 895-900, 2010.
[14] J. K. Aggarwal, and N. Nandhakumar, On the computation of motion from sequences of images-a review, Proceedings of the IEEE, vol. 76, no. 8, pp. 917-935, 1988.
[15] J. Barron, D. Fleet, and S. Beauchemin, Performance of optical flow techniques, IJCV, vol. 12, no. 1, pp. 43-77, 1994.
[16] M. Otte, and H. H. Nagel, Optical flow estimation: advances and comparisons, In ECCV, pp. 51-60, 1994.
[17] A. Mitiche, and P. Bouthemy, Computation and analysis of image motion: A synopsis of current problems and methods, IJCV, vol. 19, no. 1, pp. 29-55, 1996.
[18] C. Stiller, and J. Konrad, Estimating motion in image sequences: A tutorial on modeling and computation of 2D motion, IEEE Signal Processing Magazine, vol. 16, no. 4, pp. 70-91, 1999.
[19] B. Horn, and B. G. Schunck, Determining Optical Flow, Artificial Intelligence, vol. 17, no. 1-3, pp. 185-203, 1981.
[20] J. Shi, and C. Tomasi, Good features to track, in Proc. IEEE Computer Society Conf. on Computer Vision and Pattern Recognition, pp. 593-600, 1994.