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RAT ROBOT MOTION STATE IDENTIFICATION BASED ON A WEARABLE INERTIAL SENSOR

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Abstract

Rat robots have great potential in rescue and search tasks because of their excellent motion ability. However, most of the current rat-robot systems relay on human guidance due to variable voluntary motor behaviour of rats, which limits their application. In this study, we developed a real-time system to detect a rat robot's transient motion states, as the prerequisite for further study of automatic navigation. We built the detection model by using a wearable inertial sensor to capture acceleration and angular velocity data during the control of a rat robot. Various machine learning algorithms, including Decision Trees, Random Forests, Logistic Regression, and Support Vector Machines, were employed to perform the classification of motion states. This detection system was tested in manual navigation experiments, with detection accuracy achieving 96.70%. The sequence of transient motion states could be further used as a promising reference for offline behaviour analysis.

Keywords: inertial sensor, real-time measurement, rat robot, motion state.

1. Introduction

Bio-robot is a new type of robot based on the *Brain-Computer Interface* (BCI) technique. Microelectrodes are implanted in the peripheral or central nerval system of an animal, which can send virtual feelings to the animal through mild electrical stimulation and used for controlling the movement of a bio-robot. Using electrical stimulation as control commands, we can direct the animal to perform complex behaviours. Bio-robots have been implemented in several different creatures, including cockroaches [1], rats [2, 3], pigeons [4], goldfish [5] and so on. Bio-robots are superior to traditional mechanical robots in many aspects, such as mobility, environmental adaptability, and energy consumption, which possess great potential in rescue and search tasks [6].

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Rat-robot is one of the typical kinds of bio-robot. An operator can send control commands by computer and make the rat robot navigate along a specified path [7]. However, because of the reliance on human guidance, rat robots are largely restricted in practical applications. When human guidance is not available in some rescue and search tasks, such as under the rubble of a collapsed building, the rat robot is expected to be controlled automatically. The first step of automatic navigation is to achieve accurate identification of the motion states [8]. Nevertheless, there is no satisfactory solution yet.

At present, the conventional method for monitoring motion states is using cameras [9, 10] or inertial sensors [11–13]. When using a camera, the object being observed should generally be restricted to the laboratory environment. In our previous research, we also tried to mount a miniature camera on a rat robot [14]. We captured the scene in front of the rat and proposed a real-time video-tracking algorithm to extract its rotational direction and rotational speed. This method was somehow complicated and unstable because the rat has many unpredictable behaviours, such as assuming an upright body posture and suddenly grooming its head. Therefore, the visual method may be more suitable for obtaining environmental information rather than indirectly monitoring the rat's motion states.

Wearable inertial sensors are widely used in human posture recognition [15, 16]. Similar studies have also been done in animals [17, 18], mainly as the bio-loggers for ecological research. As these studies focused on the temporal distribution of animal behaviour, they generally analyzed the data offline. One particular study for a real-time application was a computer-assisted canine posture training system [19]. In that study, John *et al.* mounted two inertial sensors on the dog's chest and rump respectively to collect data. A threshold-based classification algorithm was used to recognize if the dog responded to the trainer's command. The system would then give proper feedback in time.

So far, inertial sensors are still rarely used in bio-robot applications with few studies about them to be found. Abhishek designed a low-cost control backpack for cyborg roach, which incorporates an inertial sensor to provide linear and rotational acceleration measurements [20]. Cole *et al.* mounted an inertial sensor on a cyborg roach and used several machine learning algorithms to identify its motion modes with offline analysis [21]. According to our investigation, inertial sensors have not been applied to rat robots yet.

In this paper, a real-time system was proposed to identify several common motion states of a controlled rat robot in a limited space. An inertial sensor was used to capture acceleration and angular velocity data. Since the system was designed for rat-robot automatic navigation, we poured attention into both detection accuracy and response latency. The system was then tested in manual navigation experiments. The results showed that it could effectively detect the rat's motion states.

The remainder of this paper is organized as follows. Section 2 describes the process of building the detection model in detail, introducing the methods of collecting data, feature extraction, and the classification algorithms we used. The experimental results are presented and discussed in Section 3. Finally, we give our conclusions and future plans in Section 4.

2. Materials and methods

2.1. Data collection

The rat robot (an adult Sprague Dawley rat, 500g) that took part in the experiments is shown in Fig. 1. To capture acceleration and angular velocity data, we redesigned the backpack and added two *inertial measurement unit* (IMU) interfaces. Two IMUs were mounted on the rat's head and body separately to obtain motion information. The IMU on the body was integrated into the backpack as attaching it directly to the hair was not feasible. No other location was considered as the rat might gnaw the devices. The IMUs used in this study were BMX160 (Bosch, Inc.), which integrates a 3-axis accelerometer, a 3-axis gyroscope, and a 3-axis geomagnetic sensor. Based on our previous experiments, the sampling rate was set to 25 Hz. The data was then sent to the computer by Bluetooth.

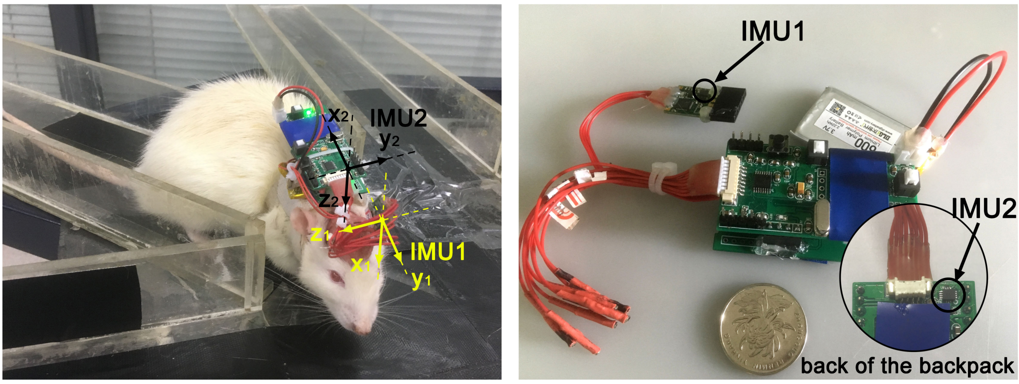

Fig. 1. The rat robot wearing IMU1 and IMU2 (left) and details of the backpack (right).

As our rat robot's target application scenario is the rescue and searching task of narrow spaces, we are interested in its motion states in a limited space. An eight-armed maze (shown in Fig. 2) was used to simulate a narrow space. The width of each arm is about 12 cm, which could limit many unexpected behaviors but has no limitation on the normal locomotion of the rat robot. As such, the middle part of the maze and the end of each arm can respectively simulate the dead-end and fork space, which we think are two important areas for automatic navigation. According to our previous research [7, 22], although the arm's wall is transparent, it does not have much influence on the rat robot's behavior.

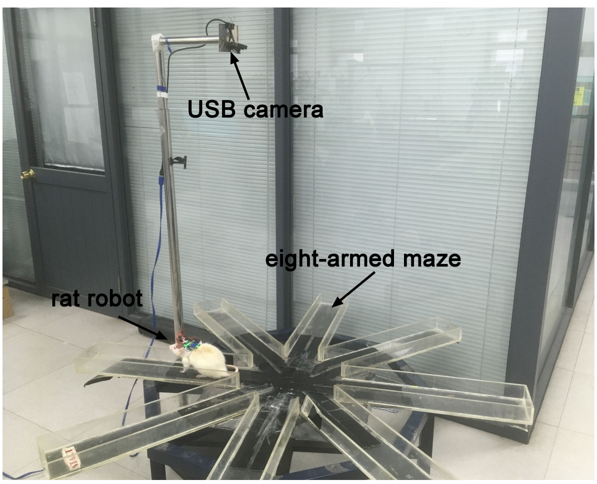

Fig. 2. The experimental site.

To simulate the actual movement states of a rat robot during a control task, the data were collected through manual navigation. An operator guided the rat robot to move in the eight-armed maze. The control commands were not always consecutive. Therefore, the rat robot might sometimes stop or groom its head. These motion states would also be recorded and detected afterward. It should be noted that when the rat robot reached the end of an arm, we would immediately send turning prompt stimulation. This was done to make the whole turning back process under control and make the amount of left and right turning balanced. The whole experimental process was captured by a USB camera above the eight-armed maze.

This study was approved by the Ethics Committee of Zhejiang University. All the experiments were performed in accordance with the guidelines issued by the Ethics Committee of Zhejiang University, and they complied with the China Ministry of Health Guide for the Care and Use of Laboratory Animals.

2.2. Motion state definition

In total, five primary motion states were studied. The description of each motion state is shown in Table 1. The distinction of walking forward, swerving, and turning back could help us judge the current whereabouts of the rat robot. We added the motion state of head grooming since it happens when the rat feels too excited, which means the electrical stimulation is too intense, and the stimulation parameters should be modified at once.

Table 1. Descriptions of the aim motion states.

Motion state category	**Description**
Walking forward	The rat moves forward by advancing its feet alternately at a slow pace. This behavior mainly occurs in the straight road of the eight-armed maze.
Swerving	The rat moves from one arm to the next one. Its body rotates about 135 degrees clockwise or counterclockwise. This behavior happens at the fork of the eight-armed maze.
Turning back	The rat's body rotates about 180 degrees clockwise or counterclockwise in the same spot. This behavior mainly occurs at the end of an arm.
Stopping	The rat changes postures without changing its location. It may sniff around or lie down in a relaxed position.
Head grooming	The rat rears and grooms its head with upper limbs.

However, it is not appropriate to train the classification model directly using the above motion state categories. The swerving and turning back process usually lasts over one second, which would result in unbearable response latency in the system. Our method was to detect transient motion states firstly and then distinguish swerving and turning back according to the sequence of the predicted results. This method is similar to Carroll *et al.*'s way to some degree [23]. By observing the rat's behavioral pattern, the transient turning states were divided into turning in the same spot and turning with moving. The most typical moments for these two transient motion states are the middle moment of the turning back process and the middle moment of the swerving process respectively. In other words, we would directly classify seven transient motion states, including *walking forward* (WF), *turning left in the same spot* (TLSS), *turning right in the same spot* (TRSS), *turning left with moving* (TLM), *turning right with moving* (TRM), *stopping* (S), and *head grooming* (HG). The detection results could be used for real-time applications. We then would distinguish swerving and turning back by the predicted results sequence, applying it to offline behaviour analysis.

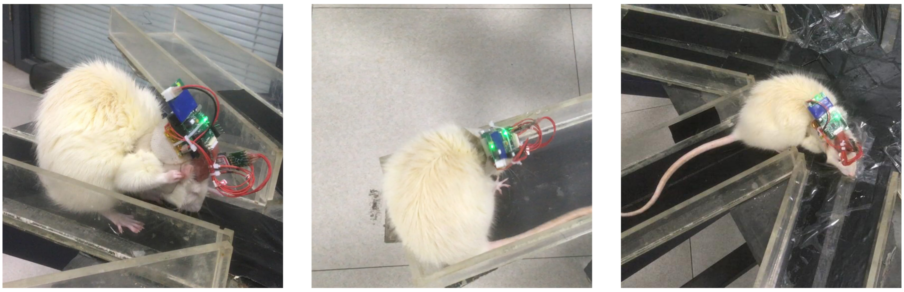

Fig. 3. Some aim motion states. Head grooming (left), turning back (middle) and swerving (right).

2.3. Feature extraction

The recorded inertial data were annotated manually based on the synchronous experimental video. Features were extracted within a specific time window (shown in Fig. 4). It should be noted that to make the label more objective, every time window contains only one pure motion state. Therefore, in the annotation, only the middle moment of the turning back process was marked as turning in the same point, and only the middle moment of the swerving process was marked as turning with moving. Transition states are not considered for the time being.

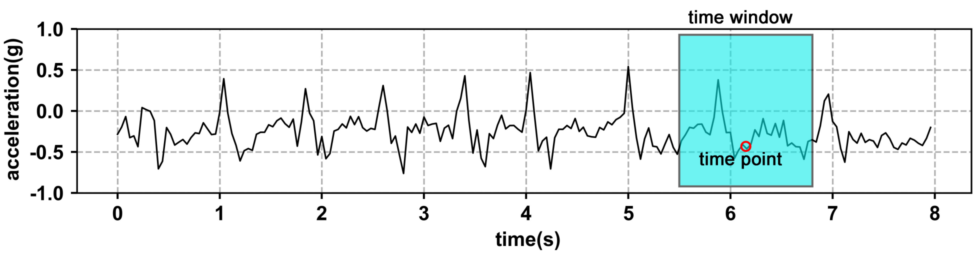

Fig. 4. Extract features within a specific time window.

Only time-domain features were considered as they are less computationally intensive than frequency-domain features. Features included mean, standard deviation, maximum value, minimum value, kurtosis, and energy for each axis [24–26]. Besides, pairwise correlations between the accelerometer's three axes and between the gyroscope's three axes were also considered [27]. A total of 42 variables were used in modelling for motion state classification.

2.4. Classification methods

We used four common machine learning algorithms to do the classification: *Decision Trees* (DT) [28], *Random Forests* (RF) [29], *Logistic Regression* (LR) [30], and *Support Vector Machines* (SVM) [31]. These methods have been widely used to deal with inertial data both in human posture recognition [26] and in wildlife observation [18, 32–34]. The machine learning algorithms were implemented using the Python scikit-learn package. To do the multi-class classification, we implemented LR and SVM using the one-vs-rest approach. The classification results would be assigned to one of four categories: TP (*True positive*), TN (*True negative*), FP (*False positive*), and FN (*False negative*). Accuracy (=[TP+FN]/[TP+TN+FP+FN]) would be presented to indicate the performance of the model [33].

3. Results and discussion

3.1. Motion state measurements

A total of 1508 motion state observations were extracted by manual annotation, each belonging to a single motion state category. The details of the dataset are shown in Table 2. Typical sample signals of the two IMUs for walking forward, stopping, and head grooming are shown in Fig. 5.

Table 2. The number of observations in the dataset.

Motion state	**Walking forward**	**Turning left in the same spot**	**Turning right in the same spot**	**Turning left with moving**	**Turning right with moving**	**Stopping**	**Head grooming**
Abbreviation	WF	TLSS	TRSS	TLM	TRM	S	HG
Samples	189	166	159	241	161	472	120

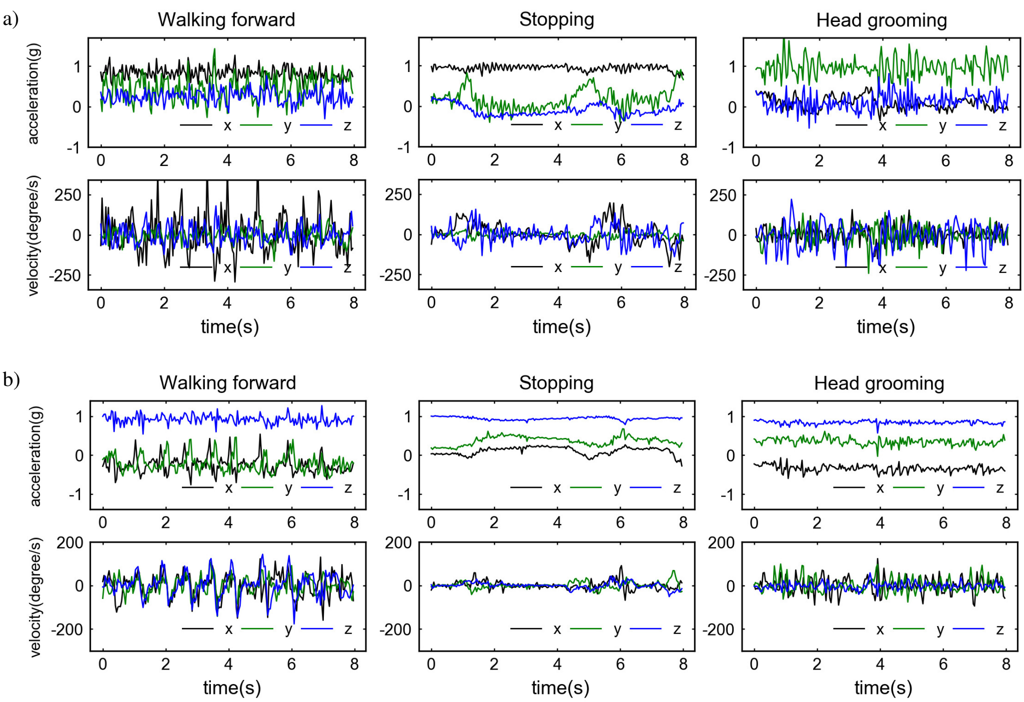

Fig. 5. Sample IMU signals for walking forward, stopping, and head grooming. The direction of the axes is defined in Fig. 1: a) sample signals of the head IMU, b) sample signals of the body IMU.

3.2. Offline model performance evaluation

To build the classification model, the dataset was randomly split into two subsamples: training dataset (70%) and validation dataset (30%). The tuning of the model parameters was performed by ten-fold cross-validation. Through parameter optimization, the tree depth in DT and RF was set to 5, and RF was applied with 20 trees. We evaluated the offline performance of the classification model with various time window sizes on the validation dataset. The results are shown in Fig. 6.

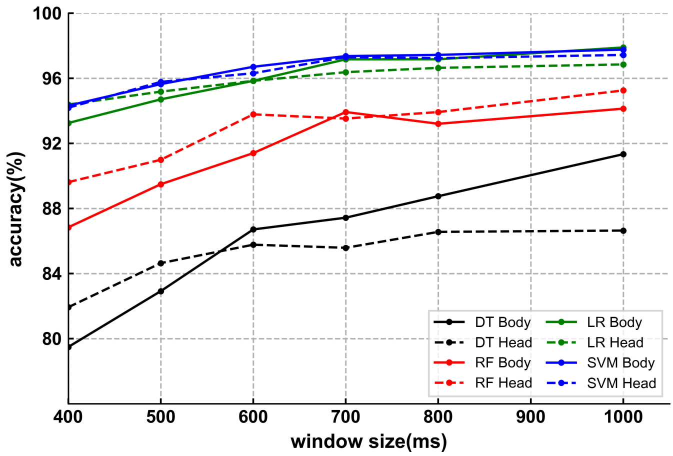

Fig. 6. Average classification accuracy over varying model parameters.

LR and SVM show better performance than DT and RF under the same conditions. When the window size is over 600 ms, the classification accuracy with RF also achieves over 90%. Therefore, RF may be a promising choice for embedded computing on wearable devices since the computational requirements of RF are much smaller [35].

The accuracy of all classification methods increases with the increase of the window size. However, a larger time window is not suitable in real online control of a rat robot. As mentioned above, there is only one pure motion state in each observation which we had selected for classification. However, in practice, a large time window may include more than one single transient motion state. A larger window also results in larger lag time in prediction. Therefore, we finally optimized the time window size to 600 ms. The latency in prediction would be around 300 ms. We tentatively considered this response latency to be bearable in most cases for the automatic navigation system. According to our investigation, in some real-time human posture recognition cases, their classification system's window size is around 1 second [26, 36].

Two different sensor locations were tested in the experiments. The results are shown in Fig. 6 by solid lines and dashed lines. The difference in accuracy is not significant in most cases. Although the motion pattern of the head and body is quite different, it seems that machine learning algorithms could handle it quite well.

Based on the above results, we used the IMU integrated into the backpack and trained an SVM classification model with a window size of 600 ms. These parameters would also be used to build the online detection system in Section 3.3. The classification model was tested on the validation dataset, and the results are presented in a confusion matrix in Fig. 7. The rows indicate the observed motion states, whereas the columns indicate the predicted results. The correct results are shown in the diagonal. The classification accuracy of our model achieves 96.70%. Most misclassifications occur between the two turning states. This may be because their signals are somewhat similar, and they usually occur consecutively in the timeline.

A comparison of our method with some methods mentioned in the introduction is shown in Table 3. As these methods were designed for specific animals, they vary comparatively in the choice of sensors and the range of behaviours studied. In relative terms, our method can

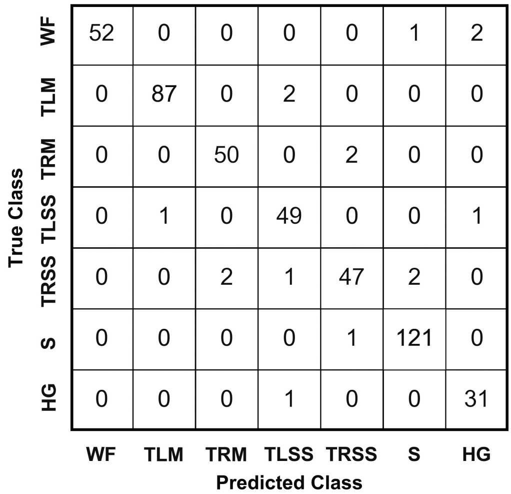

Fig. 7. Confusion matrix of the classification results.

distinguish several different motion states with only one sensor site. It also performs well in terms of accuracy and response latency at the same time. The overall performance is satisfactory.

Table 3. Behaviour detection systems designed for different animals.

Reference	**Current study**	[21]	[19]	[18]
Animals	Rat robots	Cyborg roaches	Dogs	Eurasian beavers
Sensors	An accelerometer and a gyroscope	An accelerometer and a gyroscope	Two accelerometers and two gyroscopes	An accelerometer
Behaviours	Walking forward, turning in the same spot, turning with moving, stopping, head grooming	Stopping, clockwise movement, counter-clockwise movement, free movement	Sitting down	Standing, walking, swimming, feeding, grooming, diving, sleeping
Classification Method	Support Vector Machines	Support Vector Machines	A variance-based threshold classifier	Random Forests
Window size	600 ms	1.5 s	400 ms	2 s
Real-time system	Yes	No	Yes	No
Offline accuracy	96.70%	93.02%	97.3%	94.99%

3.3. Online model performance evaluation

As mentioned above, swerving and turning back would be distinguished by the sequence of transient motion states. To make the sequence more distinguishable, a 50% overlapping sliding window was used when building the online model. Because each time window may include multiple motion states, especially in the transition between two motion states, manual annotation is not objective for consecutive inertial data. Therefore, we directly evaluated the predicted sequence of the results, focusing on whether it is consistent with reality.

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The typical transient motion state sequence of swerving and turning back is shown in Table 4. From the sequence with overlapping windows, it is clear that the process of turning back is dominated by turning in the same spot while the process of swerving is dominated by turning with moving.

Table 4. Typical transient motion state sequence of swerving and turning back.

Motion state	**non-overlapping windows**	**50% overlapping windows**
Turning back (left)	TLSS-TLSS-TLSS	**TLM-TLSS**-TLSS-TLSS-TLSS-TLSS
Swerving (left)	TLSS-TLM-TLM	**TLSS-TLM**-TLM-TLM-TLM-WF
Turning back (right)	TRSS-TRSS-TRSS	**TRSS-TRSS**-TRSS-TRSS-TRSS-TRSS
Swerving (right)	TRM-TRM-TRM	**TRM-TRM**-TRM-TRM-TRM-WF

Besides, because the *medial forebrain bundle* (MFB) electrical stimulation is only given on one side of the brain, the rat tends to turn to the contralateral direction inherently [37]. As shown in Table 4 in the bold font, the turning pattern is slightly different between left and right turning. Turning back (left) starts with a turning with moving while turning back (right) starts with a turning in the same spot. This phenomenon is similar during the swerving process. As the sequence could provide some movement details, we think this method is likely to be used in other behavior analysis applications in the future.

We tested the online detection system in manual navigation experiments. Figure 8 shows the trajectory and the real-time predicted motion states when the rat robot moved from point A, turned round on point B, and finally reached point C. Figure 9 shows the actual movement of the rat robot. Compared with the experimental video, the predicted results were basically consistent with the actual behaviours. In general, swerving and turning back could be clearly distinguished from the sequence. There is a red point at the fork position marked as turning right in the same spot. According to the experimental video, this is because the rat robot briefly turned to the right

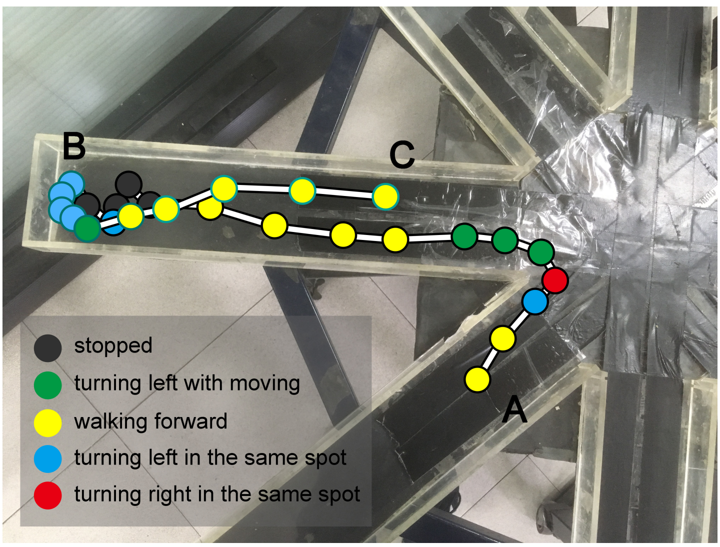


Fig. 8. The trajectory and predicted results when the rat robot moved from point A to point C.

side at that moment (shown in Fig. 9b). And the classification model accurately captured this behavior. Besides, from the spatial distribution of the points, it seems that different motion states generally occurred in specific locations. The sequence may provide a reference for speculating the position of the rat robot.

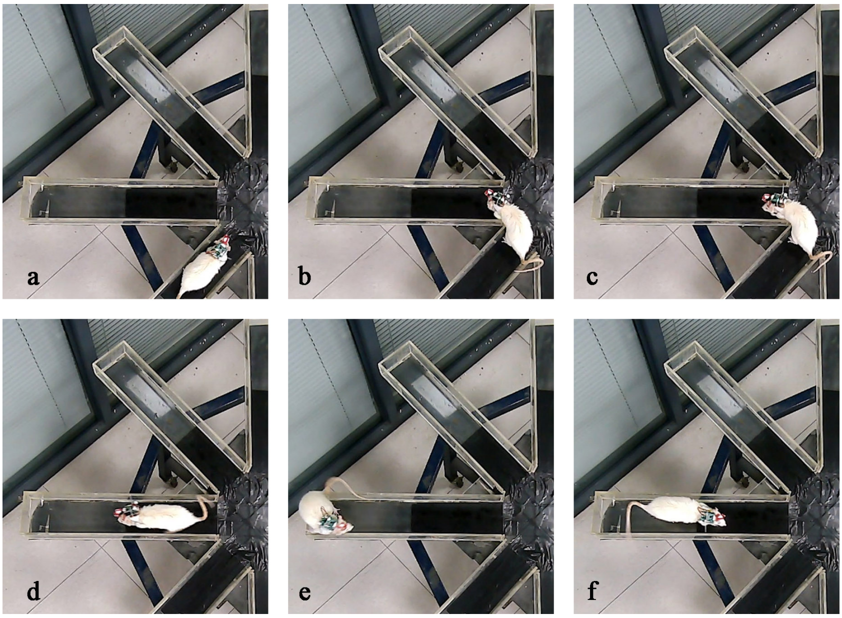


Fig. 9. The actual movement of the rat robot.

4. Conclusion and future work

In this paper, a real-time detection system for a rat robot was proposed. Our system can effectively detect several different common motion states of the rat robot based on a wearable inertial sensor. The experimental results also suggested that some long-lasting behaviours could be distinguished according to a sequence of transient motion states. This work is the prerequisite for rat-robot automatic navigation. The predicted motion states could provide evidence for automatically selecting commands. This method also shows excellent potential in training as the sequence could directly provide some movement details. To the best of our knowledge, this is the first work to use an inertial sensor in a rat-robot system.

However, it should be noted that our system has only been examined in the eight-armed maze, and the rat robot was still controlled by an operator during the trial. When a rat robot is automatically controlled in the actual situation afterward, its motion states will undoubtedly be more complicated. Besides, as the rat robot's behaviours are occasionally discontinuous, the motion state sequence may not always be visualized. Despite its preliminary character, our work has clearly indicated that using an inertial sensor to detect the real-time motion states of a rat robot is promising.

Building on our current results, some further work is needed. Firstly, we will add some other behaviours in the system, such as digging, going uphill and downhill. These behaviours are decided by specific applications. Secondly, we are interested in optimizing the method of sequence analysis. Last but not least, the classification model could be simplified and integrated into an embedded backpack. As mentioned above, Random Forests may be a suitable choice. In general, our ultimate goal is to implement a rat-robot automatic navigation system in the future.

References

[1] Latif, T., & Bozkurt, A. (2017). Roach Biobots: Toward Reliability and Optimization of Control. *IEEE Pulse*, *8*(5), 27–30. https://doi.org/10.1109/mpul.2017.2729413

[2] Talwar, S. K., Xu, S., Hawley, E. S., Weiss, S. A., Moxon, K. A., & Chapin, J. K. (2002). Rat Navigation Guided by Remote Control. *Nature*, *417*(6884), 37–38. https://doi.org/10.1038/417037a

[3] Koo, B., Koh, C. S., Park, H., Lee, H., Chang, J. W., Choi, S., & Shin, H. (2017). Manipulation of Rat Movement via Nigrostriatal Stimulation Controlled by Human Visually Evoked Potentials. *Scientific Reports*, *7*(1), 2340–2347. https://doi.org/10.1038/s41598-017-02521-6

[4] Cai, L., Dai, Z., Wang, W., Wang, H., & Tang, Y. (2015). Modulating Motor Behaviors by Electrical Stimulation of Specific Nuclei in Pigeons. *Journal of Bionic Engineering*, *12*(4), 555–564. https://doi.org/10.1016/S1672-6529(14)60145-1

[5] Zhang, C., Liu, J., Tian, H., Kang, X., Rui, Y., Yang, B., Zhu, H., & Yang, C. (2013). Control of Swimming in Crucian Carp: Stimulation of the Brain Using an ImplantableWire Electrode. *The 8th Annual IEEE International Conference on Nano/Micro Engineered and Molecular Systems*, China, 360–363. https://doi.org/10.1109/NEMS.2013.6559751

[6] Bozkurt, A., Lobaton, E., & Sichitiu, M. (2016). A Biobotic Distributed Sensor Network for Under-Rubble Search and Rescue. *Computer*, *49*(5), 38–46. https://doi.org/10.1109/MC.2016.136

[7] Feng, Z., Chen, W., Ye, X., Zhang, S., Zheng, X., Wang, P., Jiang, J., Jin, L., Xu, Z., Liu, C., Liu, F., Luo, J., Zhuang, Y., & Zheng, X. (2007). A Remote Control Training System for Rat Navigation in Complicated Environment. *Journal of Zhejiang University - SCIENCE A*, *8*(2), 323–330. https://doi.org/10.1631/jzus.2007.A0323

[8] Zhang, X., Sun, C., Zheng, N., Chen, W., & Zheng, X. (2012). Motion States Extraction with Optical Flow for Rat-Robot Automatic Navigation. *2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, USA, 976–979. https://doi.org/10.1109/EMBC.2012.6346096

[9] Camalan, S., Sengul, G., Misra, S., Maskeliunas, R., & Damasevicius, R. (2018). Gender Detection Using 3D Anthropometric Measurements by Kinect. *Metrology and Measurement Systems*, *25*(2), 253–267. https://doi.org/10.24425/119568

[10] Wodziński, M., & Krzyżanowska, A. (2017). Sequential Classification of Palm Gestures Based on A* Algorithm and MLP Neural Network for Quadrocopter Control. *Metrology and Measurement Systems*, *24*(2), 265–276. https://doi.org/10.1515/mms-2017-0021

[11] Wang, D., Dong, Y., Li, Q., Wu, J., & Wen, Y. (2018). Estimation of Small Uav Position and Attitude with Reliable In-Flight Initial Alignment for MEMS Inertial Sensors. *Metrology and Measurement Systems*, *25*(3), 603–616. https://doi.org/10.24425/123904

[12] den Uijl, I., Gómez Álvarez, C. B., Bartram, D., Dror, Y., Holland, R., & Cook, A. (2017). External Validation of a Collar-Mounted Triaxial Accelerometer for Second-By-Second Monitoring of Eight Behavioural States in Dogs. *Plos One*, 12(11), e188481. https://doi.org/10.1371/journal.pone.0188481

[13] Valentin, G., Alcaidinho, J., Howard, A. M., Jackson, M. M., & Starner, T. E. (2015). Towards a Canine-Human Communication System Based on Head Gestures. *The 12th International Conference ACM*, USA, 1–6. https://doi.org/10.1145/2832932.2837016

[14] Wang, Y., Lu, M., Wu, Z., Tian, L., Xu, K., Zheng, X., & Pan, G. (2015). Visual Cue-Guided Rat Cyborg for Automatic Navigation. *IEEE Computational Intelligence Magazine*, *10*(2), 42–52. https://doi.org/0.1109/MCI.2015.2405318

[15] Gjoreski, H., Lustrek, M., & Gams, M. (2011). Accelerometer Placement for Posture Recognition and Fall Detection. *2011 Seventh International Conference on Intelligent Environments*, UK, 47–54. https://doi.org/10.1109/IE.2011.11

[16] Patel, M., Pavic, A., & Goodwin, V. A. (2020). Wearable Inertial Sensors to Measure Gait and Posture Characteristic Differences in Older Adult Fallers and Non-Fallers: A Scoping Review. *Gait & Posture*, *76*, 110–121. https://doi.org/10.1016/j.gaitpost.2019.10.039

[17] Nathan, R., Spiegel, O., Fortmann-Roe, S., Harel, R., Wikelski, M., & Getz, W. M. (2012). Using Tri-Axial Acceleration Data to Identify Behavioral Modes of Free-Ranging Animals: General Concepts and Tools Illustrated for Griffon Vultures. *Journal of Experimental Biology*, *215*(6), 986–996. https://doi.org/10.1016/10.1242/jeb.058602

[18] Graf, P. M., Wilson, R. P., Qasem, L., Hackländer, K., & Rosell, F. (2015). The Use of Acceleration to Code for Animal Behaviours; A Case Study in Free-Ranging Eurasian Beavers Castor fiber. *Plos One*, *10*(8), e136751. https://doi.org/10.1371/journal.pone.0136751

[19] Majikes, J., Brugarolas, R., Winters, M., Yuschak, S., Mealin, S., Walker, K., Yang, P., Sherman, B., Bozkurt, A., & Roberts, D. L. (2017). Balancing Noise Sensitivity, Response Latency, and Posture Accuracy for a Computer-Assisted Canine Posture Training System. *International Journal of Human-Computer Studies*, *98*, 179–195. https://doi.org/10.1016/j.ijhcs.2016.04.010

[20] Dutta, A. (2019). Cyborgs: Neuromuscular Control of Insects. *2019 9th International IEEE/EMBS Conference on Neural Engineering (NER)*, USA, 682–685. https://doi.org/10.1109/NER.2019.8717133

[21] Cole, J., Mohammadzadeh, F., Bollinger, C., Latif, T., Bozkurt, A., & Lobaton, E. (2017). A Study on Motion Mode Identification for Cyborg Roaches. *ICASSP 2017*, USA, 2652–2656. https://doi.org/10.1109/ICASSP.2017.7952637

[22] Yu, Y., Pan, G., Gong, Y., Xu, K., Zheng, N., Hua, W., Zheng, X., & Wu, Z. (2016). Intelligence-Augmented Rat Cyborgs in Maze Solving. *Plos One*, *11*(2), e147754. https://doi.org/10.1371/journal.pone.0147754

[23] Carroll, G., Slip, D., Jonsen, I., & Harcourt, R. (2014). Supervised Accelerometry Analysis Can Identify Prey Capture by Penguins at Sea. *Journal of Experimental Biology*, *217*(24), 4295–4302. https://doi.org/10.1242/jeb.113076

[24] Watanabe, S., Izawa, M., Kato, A., Ropert-Coudert, Y., & Naito, Y. (2005). A New Technique for Monitoring the Detailed Behaviour of Terrestrial Animals: A Case Study with the Domestic Cat. *Applied Animal Behaviour Science*, *94*(1–2), 117–131. https://doi.org/10.1016/j.applanim.2005.01.010

[25] Martiskainen, P., Järvinen, M., Skön, J., Tiirikainen, J., Kolehmainen, M., & Mononen, J. (2009). Cow Behaviour Pattern Recognition Using a Three-Dimensional Accelerometer and Support Vector Machines. *Applied Animal Behaviour Science*, *119*(1–2), 32–38. https://doi.org/10.1016/10.1016/j.applanim.2009.03.005

[26] Capela, N. A., Lemaire, E. D., & Baddour, N. (2015). Feature Selection for Wearable Smartphone-Based Human Activity Recognition with Able bodied, Elderly, and Stroke Patients. *Plos One*, *10*(4), e124414. https://doi.org/10.1371/journal.pone.0124414

[27] Ladds, M. A., Thompson, A. P., Slip, D. J., Hocking, D. P., & Harcourt, R. G. (2016). Seeing It All: Evaluating Supervised Machine Learning Methods for the Classification of Diverse Otariid Behaviours. *Plos One*, *11*(12), e166898. https://doi.org/10.1371/journal.pone.0166898

[28] Breiman, L., Friedman, J. H., Olshen, R. A., & Stone, C. J. (1984). *Classification and Regression Trees*. Wadsworth and Brooks.

Metrol. Meas. Syst., Vol. 28 (2021), No. 2, pp. 255–268
DOI: 10.24425/mms.2021.136605

[29] Breiman, L. (2001). Random Forests. *Machine Learning*, *1*(45), 5–32. https://doi.org/10.1023/A:1010933404324

[30] Hosmer, D. W., & Lemeshow, S. (2000). *Applied Logistic Regression*. Wiley-Interscience. https://doi.org/10.1002/0471722146

[31] Cortes, C., & Vapnik, V. (1995). Support-Vector Networks. *Machine Learning*, *3*(20), 273–297. https://doi.org/10.1007/BF00994018

[32] Wang, Y., Nickel, B., Rutishauser, M., Bryce, C. M., Williams, T. M., Elkaim, G., & Wilmers, C. C. (2015). Movement, Resting, and Attack Behaviors of Wild Pumas are Revealed by Tri-Axial Accelerometer Measurements. *Movement Ecology*, *3*(1), 2. https://doi.org/10.1186/s40462-015-0030-0

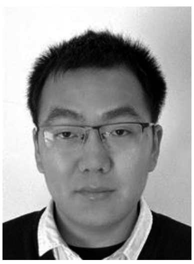
[33] Peng, Y., Kondo, N., Fujiura, T., Suzuki, T., Wulandari, Yoshioka, H., & Itoyama, E. (2019). Classification of Multiple Cattle Behavior Patterns Using a Recurrent Neural Network with Long Short-Term Memory and Inertial Measurement Units. *Computers and Electronics in Agriculture*, *157*, 247–253. https://doi.org/10.1016/j.compag.2018.12.023

[34] McClune, D. W., Marks, N. J., Wilson, R. P., Houghton, J. D., Montgomery, I. W., McGowan, N. E., Gormley, E., & Scantlebury, M. (2014). Tri-Axial Accelerometers Quantify Behaviour in the Eurasian Badger (Meles meles): Towards an Automated Interpretation of Field Data. *Animal Biotelemetry*, *2*(1), 5. https://doi.org/10.1186/2050-3385-2-5

[35] Kuppers, F., Albers, J., & Haselhoff, A. (2019). Random Forest on an Embedded Device for Real-Time Machine State Classification. *2019 27th European Signal Processing Conference (EUSIPCO)*, Spain. https://doi.org/10.23919/EUSIPCO.2019.8902993

[36] Chereshnev, R., & Attila, K. (2018). RapidHARe: A Computationally Inexpensive Method for Real-Time Human Activity Recognition from Wearable Sensors. *Journal of Ambient Intelligence and Smart Environments*, *5*(10), 377–391.

[37] Sun, C., Zhang, X., Zheng, N., Chen, W., & Zheng, X. (2012). Bio-Robots Automatic Navigation with Electrical Reward Stimulation. *2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, USA, 348–351. https://doi.org/10.1109/EMBC.2012.6345940



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