33rd Annual International Conference of the IEEE EMBS
Boston, Massachusetts USA, August 30 - September 3, 2011

An Automatic Control Model for Rat-robot

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***Abstract*—In this paper, a control model is developed to automate the process of navigation in rat-robot-a new type of bio-robot based on BCI(Brain-Computer Interface) technique. Because of the particular difficulties in rat-robot control, we design a novel control model to 'learn' and 'imitate' the control behavior of human guidance. General Regression Neural Network (GRNN) model is used to analyze the control commands made by human operators, with the locomotion information of rat-robot recorded and analyzed in a video-based experimental system. The results of the control model shows that the human control process could be well understood and predicted, and expected to generate control commands automatically in future real-time rat-robot navigation experiments.**

I. INTRODUCTION

Brain Computer Interface (BCI) provides a new approach to implement the direct interaction between the outer devices and the brains of animals[1-3]. Based on this technique, a new type of bio-robot system has been developed. Through micro-electrodes implanted in the brain and mild electrical stimulation of specific region, some 'virtual' feelings could be directly generated within the brain of the animals. After a reinforcement training process, animals could be controlled by human operators to perform complex behaviors, such as swim, fly, or walk along certain route. In recent years, BCI-based bio-robot systems are implemented in several different kinds of creatures, including cockroaches[4], rats[5-10], sharks[11-12], pigeons[13], cows[14] and geckos[15].

Tawlar developed the first BCI-based rat-robot navigation system in 2002[16]. Micro-electrodes are implanted into the medial fore-brain bundle(MFB) in rat's brain, in which stimulation generates intense excitement as a virtual reward to train the animals. The same rat also received the electrodes in both left and right somatosensory cortices (SI) whisker representations to make the rat feel the 'virtual touch' in the responding direction. With both the 'reward' and 'cue' stimulation, the rat-robot could be trained to make certain behavior, such as walking over defined routes, even in 3-D terrains. In our previous work, rat-robots performs several behaviors following human instructions, such as '*walk forward*', '*turn left'* or *'right*', and even '*freeze*' in the certain circumstance[10].

As a new type of robotics system, rat-robot shows huge potential in many applications, as in searching and rescue area. Naturally, it is expected to perform more tasks controlled by computers automatically. However, the state-of-the-art rat-robot still relies on the human guidance.

The automatic navigation of the rat-robot is difficult to implement and very error prone. Unlike traditional mechanical robots, the executive of rat-robots are awake animals with self-consciousness and high intelligence. Stimulation are more like 'cues' to induce the animals to perform certain behavior, rather than strict, full-executed 'commands' which transfers directly into electrical or mechanical response in traditional robotics. The effect of stimulation is subject to several factors, e.g. the effects of implantation surgery, the training process through which the rat-robot learns to understand and react to stimulation, and inner physical and intelligent differences between animal individual. It makes the navigation process full of uncertainties and unpredictability. The human operators have to observe and identify the motion of rats, as location, head orientation, and other features to determine whether or what commands should be given to rat-robot. The decision logic is difficult to model. Some automatic control theories and methods in traditional robotics[22-23] are not suitable in the navigation of bio-robots. In addition, the body of rat-robot is non-rigid and multi-variant. It makes huge challenges in the information extraction and analysis of the rat-robot's motion. Without precise motion parameters, the control decision is difficult to make, and the feedback of control command is impossible to be evaluated.

To implement the automatic navigation of rat-robot, the control algorithm need to extract and analyze the motion of the animal, and generate control commands like human operators according to these information. The 'fuzzy' control logic hidden beneath the human control decision-making process should be well modeled and quantized.

Neural networks have been widely used to control and model in robotics, not only in traditional mechanical robots or vehicles, but also in animals[17-18]. Remarkably, a GRNN is used to model the control process of a canine and later the automatic navigation is achieved in freely canines[24]. In this paper, GRNN model is utilized to analyze the human control data to 'learn' and 'imitate' the manual controlling process. During the rat-robot navigation guided by human, both the experimental video and the commands sent by operator are recorded. With image processing technique, some

Manuscript received on March 26, 2011. The work of this article was supported by grants from the National Natural Science Foundation of China (No. 60873125, 30800287, 61031002, 61001172), Zhejiang provincial key science and technology program for international cooperation(No. 2011C14005), Zhejiang Provincial Natural Science Foundation of China (No. Y2090707), the Fundamental Research Funds for the Central Universities, and the China Postdoctoral Science Foundation (No. 20090461369, 201003725).

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fundamental motion information is extracted and normalized as the input of control model. The corresponding commands at the same moment are synchronized as the 'label' of the motion data. After training, the GRNN model is expected to predict the human control decision. Experimental result shows that the model works well with high accuracy. The next step and the ultimate goal is to utilize this model to achieve auto-navigation of rat-robot in real time.

The remainder part of this paper is organized as follows. Session II describes the details of the control model, both the data structure and the algorithm. Session III introduces briefly the experiment of rat-robot and the navigation system we developed. The experimental result of the control model will be discussed in Session IV. Session V will be the conclusion and our future plan.

II. CONTROL MODEL

A. Data in the Model

Two types of data are used to build our control model, the locomotion information of the rat-robot as the input data to the model, and the control commands the operators actually gave, as the classification labels of the model.

In traditional mechanical robotics, the locomotion information could be represented by two parameters, the position and the orientation of the robot. With these parameters, the robot could be well navigated in most situation. In our rat-robot study, the rat's position $\boldsymbol{x}$ and the head orientation $\boldsymbol{\theta}$ are also significant. These two parameters are obtained using a bird-eye camera and image processing technique (details in Session III). However, whether the position $\boldsymbol{x}$ and head orientation $\boldsymbol{\theta}$ are enough for navigation has to be examined. We assume that with only these two parameters the navigation could be well accomplished, and set up a serial of experiments to verify our assumption.

In manual navigation, we use a camera to record the entire environment. The video captured is then processed to obtain the position and orientation of the rat-robot. Meanwhile, we cut the body of rat-robot off the image, and replace it by a simple graphics which contains basic locomotion (the center of the body, center of head and the orientation angle) in every frame of the video as shown in Figure 1. The human operators observe the processed video instead of the real environment to control the rat-robot to follow certain routes. Experimental results show that in this experimental set, operators work well. The success rate of navigation based on the processed video is almost 100 %. It proves that in rat navigation no more data is essential.

Besides the locomotion parameters, we also take some other information as the input to our control model. The route is given before the navigation, and divides by some way point, where the rat-robot is expected to turn to other direction. The distance (D) represents the length between the head of the rat and next way point in image coordinate system. Notice that the distance is logical length in image coordinates system, as the number of pixels in the frame. The expected angle (EA) is defined as angle rat expected to turn in next way point. And

Fig. 1. The video with the position and orientation is computed and marked colored (left); the processed video with which the body of rat-robot is replaced by a rectangle, and a red line points to the head's direction.

route angle (RA) is the angle between the rat's orientation and the current route direction. In addition, to avoid over-frequent stimulation harming the rat's brain, the time interval since last command (T) is also taken account of.

All the data is processed into a vector with several dimensions shown in Table I. As the input to the GRNN, the angles in vector are normalized by degree of 360, with others using the highest known values of a given attribute as maximum.

The human control commands are recorded and synchronized with the locomotion information. Because in single navigation experiment, the specific simulation parameters (such as the width, intensity, vibration frequency of stimulus) are constant, the command is represented by the code of the type shown in Table II.

B. General Regression Neural Network

General regression neural network (GRNN) is a memory-based network that provides estimates of continuous variables that dependent on representative training instances. It is a one-pass neural network which iterations are not necessary[21].

Each training instance in the GRNN consists of a vector X, in our control model, X is the vector of locomotion information, consisting training elements shown in Table I. The output Y is an estimated value as result, and in our control model, Y is the command expected to be sent to the rat-robot. To provide an estimation of the value of Y.

Table I

Name	Units
position x	pixels
position y	pixels
orientation	degree
distance (D)	pixels
expected angle (EA)	degree
route angle (RA)	degree
time since last comm (T)	ms

Table II

Command	Description	Code
NULL	No command	0
FORWARD	Move forward	1
LEFT	Turn left	2
RIGHT	Turn right	3

For vector X, the result is calculated as:

$$Y(X)=\frac{\sum_{i=1}^{n} Y_i * \exp(-\frac{D_i}{\sigma})}{\sum_{i=1}^{n} \exp(-\frac{D_i}{\sigma})} \quad (1)$$

where n is the number of training instances, Yi denotes the desired output for a given training instance vector X. σ is a called 'smooth parameter', and Di indicates the Euclidean distance between X and a given training instance vector, as shown in (2):

$$D_i=\sum_{i=1}^{m}\left|X_j-X_{ij}\right| \quad (2)$$

where Xj denotes jth element in instance vector, and Xij is the corresponding element to be classified, m is the number of elements in instance vector.

In our model, different values of σ from 0.01 to 10 are used to make cross validation. Comparing the accuracy rate, the model iterates to find the optimal value. After 10 times of iteration, the σ is optimized.

III. Experiments

The hardware setups[8], and the framework of software modules of auto-navigation system are inherited from the former work[10, 21].

A bird-eye camera is set to record the entire experimental environment. On the image captured by the camera, human operators set up the default route of each trail. The route is divided by several way points. Paths between way points are expected to be straight lines.

The current experimental environment is set on a flat blackboard. The contour of rat-robot in every video frame could be obtained well because of the intensive contrast between the color of rat and background. The mass center of the contour is computed as the position of rat-robot. We use a red hat as a marker on the rat's head so the head position can be easily detected. With these two position points we could figure out the orientation of rat-robot. The real-time detecting results are demonstrated in Fig 2. The algorithms are developed using open source library Open Computer Vision Lib (OpenCV, Intel).

The camera captures 60 frames per second (fps), with a resolution of 640 by 480 pixels. The motion analysis algorithm works well in real time. However, in practice we reduce the sample rate to 10 Hz to get the instances for model training. The reason is that compare to 60 Hz of fps, the movement of the rat is much slower. Analyzing the process of human control navigation, it is found that the operators send commands no more than 3 times in a second. So the commands are 0 (as none commands are sent) at most time. Average-time-interval sampling method will cause amounts ofmeaningful data lost. So in data sampling process, we adopt priority-based tactics to make sure that every non-zero instance with which the non-zero command must be chosen.

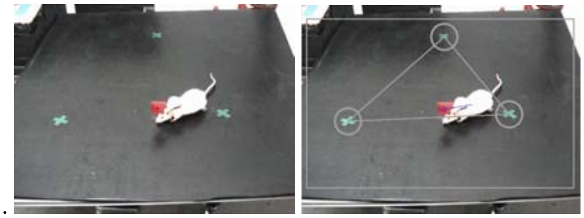

Fig. 2. (a) A frame (frame 317) captured from video; (b) the same frame processed in system to obtain the body position of rat-robot and the head position (represented by the position of red hat). A blue line are drew to connect these two points and processed results are recorded

IV. Results

In experiments, we record 6 trails of manual navigation of a rat-robot. In each trail, the rat is placed at a random way point as starting point, and then controlled by human operators manually to finish a default route. In 3 trails the rat-robot is expected to walk clockwise for 2 circles, and the other 3 for anti-clockwise. The average time length of each trail is about 60 seconds with about 200 commands. According to our sampling rate, more than 3000 instances are used to train the control model.

To test the model, we record another trail of the same rat-robot which is controlled to follow a clockwise circle (through which both 'forward' and 'turn right' commands are given). The test trail lasts 568 seconds and the rat-robot made 5 turnings in the entire experiment. We compare the prediction made by our model, with the actual control commands recorded. The result is show in the Fig 3. The prediction is correct at most 'walking forward' process(e.g. 100s-150s). The possible reason of high accuracy is that when the rat-robot is controlled to walk forward, the commands decision follows a relative definite and simple rules, i.e., the 'forward' commands should be given at intervals to induce the rat-robot to move along. The decision could be well predicted. When the rat-robot enter a way point (e.g. 310s), the model could predict and generate the turning commands correctly.

However, at some way points, the estimation is not good. The control model makes false positive prediction when the turning commands are not necessary e.g. 400s-430s. There are some potential reasons. 'Turning' stimulation is given as a virtual 'cue' to suggest the rat-robot to make a turn. According to the operational conditioned reflection based on the early training process, the rat-robot should turn to the expected direction. At that moment, 'reward' commands should be given immediately to encourage the rat to accomplish this movement. The entire process is more complicated than the 'walk forward' part. The human operators should make the control decisions based on their personal judgment, which makes the prediction with more uncertainties.

In addition, in actual real-time experiments, the operators should observe the feedback of rat-robot and adjust the command decision according to the results. However, on off-line test, the predicted commands make no effect to the behavior of rat-robot, which could make the false estimation accumulate in the test result.

As shown in the figure 3 and verified by checking the video

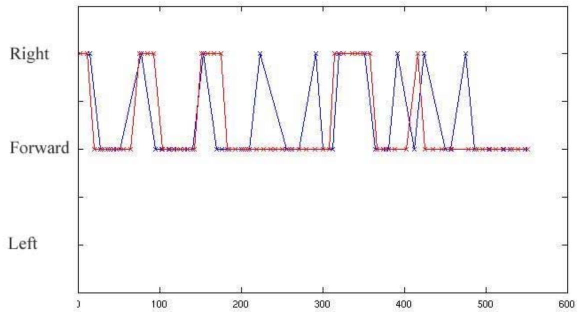

Fig. 3. The results computed by GRNN control model. The blue '*' represents a actual control command is given by the human operator, and the red '*' represents the estimated command generated by the control model.

of the experiment, the control model makes all five turning decision estimation correctly. Later three more trails are tested in the same way. The results show that although some false positive turning decisions are made, every actual 'turning' and 'forward' decision in rat-robot could be well predicted. It indicates that the control model could guide the rat-robot in automatic navigation with slight lapses.

V. Conclusion And Future Work

A novel control model for rat-robot automatic navigation is proposed in this paper. Using a GRNN, the model 'learn' the human control records and make prediction of control decision. Experimental results show that the human control commands could be predicted in navigation with a relatively high rate of accuracy. It indicates that the control model could be used in real-time automatic navigation of rat-robot without human inference. And also the control model could be used in other bio-robot automatic control to address similar problems.

This project is on relatively early stages. Based on current results, some further work should be done. Firstly, the motion information is computed according to video records. The algorithm is relative simple which suffers from poor robustness. A new computer vision-based method using optical flow tracking will be used in future work. Secondly, the control model is built to 'learn' and 'imitate' the human control process. However, the manual control process is not a 'perfect' machine. In practice, the operators may control the rat-robot with randomness because of inattention or lack of experience. In future rat-robot training, the control decision made by human operators should follow a strict set of rules. Lastly and mostly, the ultimate goal of control model is to implement the automatic navigation of rat-robot. The on-line control experiments will be taken in the future.

Acknowledgment

The authors would thank Chaonan Yu, Ning Zhao for the rats' surgery and Songchao Guo for helping training rats.

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