Development of automatic analysis and recognition of mouse behavior by segmentation and t-pattern method using video tracking

A. Cherepov and K. Anokhin
Department of Systemogenesis, P.K. Anokhin Institute of Normal Physiology, Moscow, Russia, ipmagus@mail.ru

Introduction

Automated recognition of human and animal behavior is a rapidly developing trend in behavioral researches. This recognition is of great practical importance (e.g. total video monitoring in airports and railway stations, screening researches of new drugs, etc.) and is a key element in fundamental studies of brain functions and behavior.

Since 2002 we developed a new approach to quantitative segmentation of animal behavior by automatic dissection of behavioral continuum into meaningful behavioral units [1] and developed a novel video tracking system [2]. Our approach described elsewhere A.B. Cherepov, et al. [3] is based on the functional systems theory of Peter Anokhin (FST) [4]. Our first results were presented at previous Measuring Behavior meeting [3]. The best segmentation was obtained by application of running median to find stops followed by the analysis of acceleration projection for obtaining segments in order to find points representing additional breaks and, hence, additional acts. Analysis of the video records of the segmented behavior demonstrated that the breakpoints found by this method showed the best match to the segmentation performed by an expert observer (about 85% coincidences).

The present research was conducted to develop algorithms for automatic recognition (classification) of behavioral units in locomotor behavior of mice.

Methods and results

In order to reveal automatically different classes of behavioral acts we used approach proposed by Drai et al. 2001 [5]. After primary dissection of the locomotor behavior into behavioral segments and stops between them, the distribution of the maximum speed was analyzed using Gaussian Mixture Model (GMM). This method models the distribution as a sum of several normal distributions. In our experiment, the distribution was typically bimodal, two types of behavioral segments are thus revealed (Type I and II). Type I behavioral segments (low velocity) mainly corresponded to rearings, stretchings, sniffings, groomings, etc. Information obtained by tracking of the center of mass only is insufficient to recognize each type of such low-velocity behavioral acts (Type I). Below we discuss only recognition of Type II behavioral acts. Normally, Type II acts include only running acts, but Gaussian distributions in GMM usually considerably overlap and some rearings, stretchings, and groomings can be erroneously included into Type II group. To solve this problem we applied an additional criterion named "bias threshold". Bias is the shortest distance between the start and end points of the act (Figure 1). If this shortest distance calculated for the act erroneously identified as "Type II" was below the bias threshold (3-4 cm in our tests) it is automatically included into the correct group (Type I).

In order to test the proposed algorithms we analyzed behavior of C57Bl/6 mice either under amphetamine treatment (acute administration i.p. 5 m/kg) in home cages or placed in a novel environment (new "home" cages of the same size with fresh bedding and transparent walls, "novelty group"). Mouse activity was recorded using our video tracking software. Segmentation of behavior was performed with modified version of SegmentAnalyser software containing comprehensive options for breakpoint detection, classification and visualization [4]. These experiments have shown the best match to segmentation into behavioral units performed by an expert observer (about 85% coincidences) for both behavior groups of mice (d-amphetamine-treated and placed in novel environment).

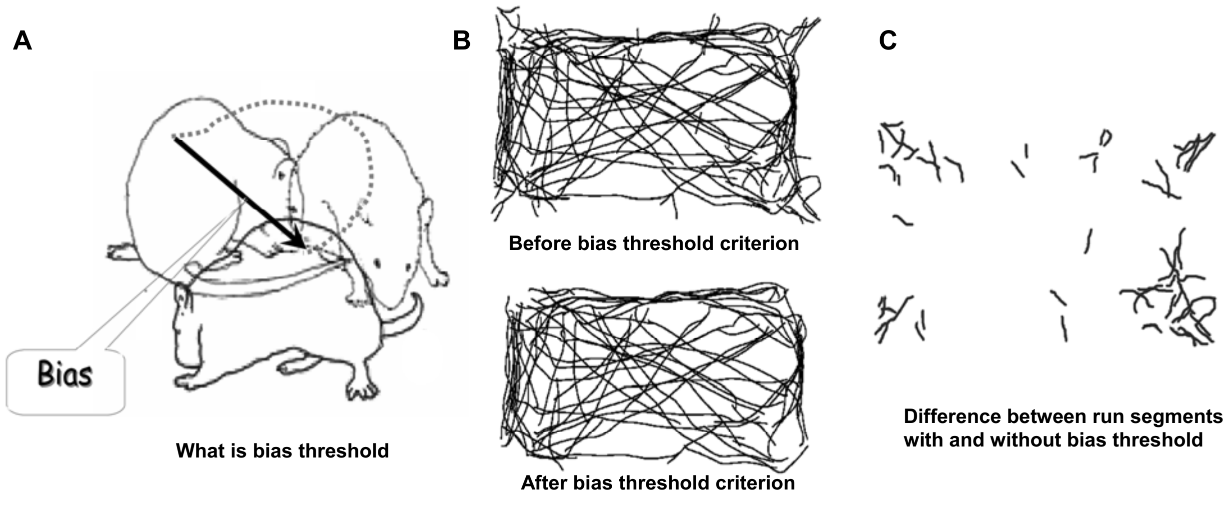

Figure 1. *Bias threshold algorithm.*

Conclusions

Bias threshold criterion allows us to correct automatic discrimination between runnings and low-speed acts, which results in 85% coincidence in automatic and expert observer's classification of behavior units.

This new algorithm is appropriate for two different mouse behavior types, and probably can be applied to analyze other types of behavior.

Ethograms obtained by expert observers were analyzed using t-pattern analysis (Theme 5.0) [6]. Behavior repertoire consisted of ten behavior units: climbing, digging, grooming, quiet, rear, rear with support, run, sniff, stretch, turn around. Two most meaningful t-patterns, "sniff-run" and "turn around-run", were detected in the behavior of both mouse groups. These t-patterns constitute about 90% of all observed patterns. Practically all runs performed by mice were components of these t-patterns. Thus, mouse behavior in these behavioral tasks can be precisely characterized by detection (manual or automatic) of all runs. And our method does allow precise automatic detection of runs!

References

1. Mukhina, T.V.; Lukashov, A.O.; Anokhin, K.V.; Bachurin, S.O. (2002). Analysis of animal path trajectories in terms of individual behavioral acts. *4th Int. Conf. on Methods and Techniques in Behavioral Research "Measuring Behavior 2002"*, Amsterdam, The Netherlands. 27-30 August, 2002.
2. Anokhin, K. and Mukhina, T. (Moscow, Russia). Development of neurocognitive interface for animal video tracking system. *5th Int. Conf. on Methods and Techniques in Behavioral Research "Measuring Behaviour 2005"*, Wageningen, The Netherlands 2005
3. A.B. Cherepov , T.V. Mukhina, K.V. Anokhin (Moscow, Russia). Automatic segmentation of mouse behavior during video tracking in home cages. *5th Int. Conf. on Methods and Techniques in Behavioral Research "Measuring Behaviour 2005"*, Wageningen, The Netherlands 2005
4. Anokhin P.K. (1968). Nodular mechanisms of functional system as self-regulatory apparatus. *Progress in Brain Research*. **22,** 230-251.
5. Drai, D.; Golani, I. (2001). SEE: a tool for the visualization and analysis of rodent exploratory behavior. *Neuroscience and Biobehavioral Reviews*. **25**, 409-426.
6. Magnusson MS (2000) Discovering hidden time patterns in behavior: t-patterns and their detection. *Behav Res Meth Instrum Comput* **32**, 93–110