# Automatic segmentation of mouse behavior using hidden Markov model

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## Abstract

A common approach to analysis of mouse behavior recorder by video tracking systems employs manual segmentation and labeling of mouse activity into behavioral acts. Developed automatic methods allow segmentation only to lingering and progression segments, suffer from poor precision and require parameter tuning. We propose a novel approach based on hidden Markov model for simultaneous segmentation and labeling of mouse trajectory into behavior acts. The method uses manually labeled video sequences for training. The developed approach has shown promising results when applied for segmentation of mouse behavior in a novel environment.

## Keywords

Video tracking, elementary behavioral acts, activity modeling, hidden Markov models (HMMs).

## Introduction

The need for high throughput behavioral screening procedures for rodents has led to introduction of automated home cages that provide various stimuli and equipped with video tracking systems [1]. This, however, results in a drastic increase in complexity regarding observation and analysis. Detailed recordings of position alone yield already an enormous set of data. Advanced analysis techniques, e.g. behavior patterns extraction and evaluation, requires segmentation of tracking data into behavioral acts. Trained human observer is required for this task. Several automatic segmentation methods have been proposed, e.g. [2], but they are restricted to distinguishing lingering and progression segments mostly. Additionally, results of manual segmentation significantly differ between experts. This limits test results replicability between labs and even between different researches in one lab.

However, in field of visual surveillance for human activities a number of approaches have been proposed for event recognition [3]. Similar methods can be applied for distinguishing behavioral acts. We propose a novel method for behavioral act recognition based on hidden Markov models [4].

## Proposed method

Our method of trajectory segmentation is based on first order hidden Markov models (HMM) [4]. This approach is an example of sequential probabilistic model and it is widely used in signal segmentation. The system (mouse) being modeled is assumed to be a process with unknown state that generates an output in the form of features, calculated from corresponding mouse trajectory. Each type of behavioral act is considered as a state of the process. The parameters of HMM are estimated from a training set of output sequences with known states. We use manually segmented trajectories with hand-labeled behavior acts as training set. 13 types of behavioral acts were identified by experts. Due to the fact that currently our tracking system can produce only x- and y-coordinates of mouse center of mass trajectory, we combined acts into 4 metastates: «Cleaning» (grooming, climbing,

digging, stretching), «Stopping» (quiet, no state, head up), «Active» (running, jumping), and «Searching» (sniffing, turning around, turning head, turning body). These states were formed basing on 4 most probable behavioral acts (mentioned at first position in the description of each metastate) and attaching the remaining ones to the most similar metastate.

We use several features, including speed, acceleration, angle between directions of speed in the current and previous time moment, angle acceleration. The likelihood function for each metastate was computed in the following way: all features were transformed to main axes (projections to eigenvectors of sample covariance matrix) in order to decorrelate them; then we estimated the density of each main axis using the mixture of 5 univariate Gaussians; finally we multiplied probability densities of each main axis to get joint density estimate. The histogram of the first main axis and the corresponding 5-gaussian approximation for metastate «Cleaning» is shown in figure 1.

The segmentation of new trajectory is performed by calculating the most probable sequence of metastates according to features which are computed for each time sample.
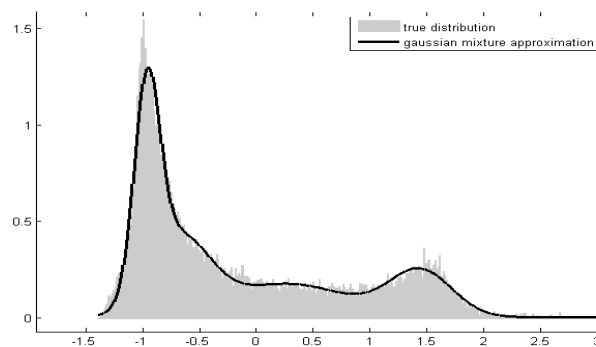


**Figure 1.** *Approximation of training sample distribution for state Cleaning and the first main axis by mixture of 5 univariate Gaussians. True distribution is shown by grey histogram and Gaussian mixture approximation is shown by black curve.*

## Experiments and future work

We have tested proposed method on 13 video sequences of bank vole exploration behavior in open field arena, 325 minutes total. 150 minutes were used as training set, and the rest as testing set. The results of automatic segmentation were compared with the manual ones, see table 1 and figure 2. These results allow us to make the following conclusions: we may classify relatively well metastates associated with fast mouse movements («Active») and with mouse stops («Stopping»). The errors in this classification happen due to the differences in detecting the borders of metastates. Two other metastates («Cleaning» and «Searching») are less distinguishable when we consider only the location of mouse center. It should be noted that different experts segment trajectories in such a way that they differ in average in 15-20% of time points. The last remark allows us to claim that our results are promising. We plan to use additional features from

**Table 1.** *Confusion matrix for mouse behavior states recognition.*

| \From class: Classified as \ | «Cleaning» | «Stopping» | «Active» | «Searching» |
|---|---|---|---|---|
| «Cleaning» | 5683 | 7120 | 22 | 3899 |
| «Stopping» | 97 | 102859 | 95 | 1883 |
| «Active» | 0 | 21 | 7590 | 1796 |
| «Searching» | 850 | 7281 | 656 | 10382 |
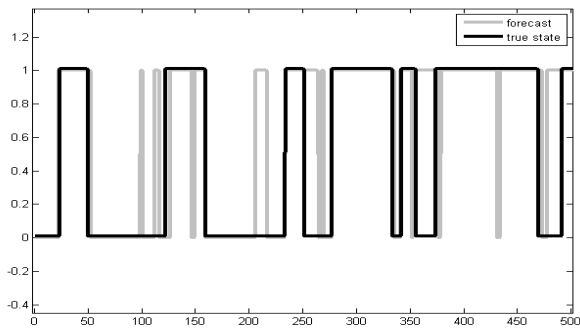


**Figure 2.** *Example of forecasting mouse trajectory states. Black curve shows right answers, grey curve corresponds to forecasted states values. For simplicity purposes only Stopping (y=1) vs all other metastates (y=0) is shown*

mouse nose and tail base points tracking to improve the accuracy and working with behavior acts directly. Also, higher order HMMs can be used to reduce the small labeling errors.

**References**

1. Spruijt B.M., DeVisser L.(2006) Advanced behavioral screening:automated home cage ethology. *Drug Discovery Today: Technologies* Vol. **3**, No. 2 2006, pp.231-237
2. Cherepov A.B., Mukhina T.V., Anokhin K.V.(2005) Automatic segmentation of mouse behavior during video tracking in home cages. *5th Int. Conf. on Methods and Techniques in Behavioral Research "Measuring Behavior 2005"*, Wageningen, The Netherlands.
3. J. Aggarwal J., Cai Q.(1999), Human motion analysis: A review. *Comput.Vis. Image Understand.*, vol. 73, no. 3, pp. 428–440.
4. Elliot R.J., Aggoun L., Moore J.B. (1995) Hidden Markov Models: Estimation and Control. *Springer*.