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An automated system for the recognition of various specific rat behaviours

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HIGHLIGHTS

- Automated recognition of the rat behaviours 'drink', 'eat', 'sniff', 'groom', 'jump', 'rear unsupported', 'rear wall', 'rest', 'twitch' and 'walk' from top-view video.
- Recognition of 71% on par with human recognition rates.
- Validation of automated recognition performed on videos recorded with different resolution, animal strain, illumination, background and cage layout.
- Validation by means of an experimental study with drug treatment and comparison of automated recognition with manual scoring by an expert.

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ABSTRACT

The automated measurement of rodent behaviour is crucial to advance research in neuroscience and pharmacology. Rats and mice are used as models for human diseases; their behaviour is studied to discover and develop new drugs for psychiatric and neurological disorders and to establish the effect of genetic variation on behavioural changes. Such behaviour is primarily labelled by humans. Manual annotation is labour intensive, error-prone and subject to individual interpretation.

We present a system for automated behaviour recognition (ABR) that recognises the rat behaviours 'drink', 'eat', 'sniff', 'groom', 'jump', 'rear unsupported', 'rear wall', 'rest', 'twitch' and 'walk'. The ABR system needs no on-site training; the only inputs needed are the sizes of the cage and the animal. This is a major advantage over other systems that need to be trained with hand-labelled data before they can be used in a new experimental setup. Furthermore, ABR uses an overhead camera view, which is more practical in lab situations and facilitates high-throughput testing more easily than a side-view setup.

ABR has been validated by comparison with manual behavioural scoring by an expert. For this, animals were treated with two types of psychopharmaca: a stimulant drug (Amphetamine) and a sedative drug (Diazepam). The effects of drug treatment on certain behavioural categories were measured and compared for both analysis methods. Statistical analysis showed that ABR found similar behavioural effects as the human observer. We conclude that our ABR system represents a significant step forward in the automated observation of rodent behaviour.

1. Introduction

Rats and mice are widely used as models for human diseases, and their behaviour is studied in laboratories around the world to find new drugs for psychiatric and neurologic disorders. Furthermore, the behavioural phenotype of transgenic rodents is used as a read-out in the search for the genetic basis of brain disorders and to reveal the underlying functional role of proteins and genes. Difficulties in the reproducibility and reliability of behavioural data have been known for a number of years (Crabbe et al., 1999; Wuerbel, 2002; Wahlsten, 2002). One of the primary sources of difficulty is the limited sustained attention of human observers, especially under dimmed light conditions, resulting in predominantly short-lasting behavioural observations. Golani and colleagues showed that a very precise ethogram and consistent time and space conditions are crucial to describe animal behaviour accurately (Drai et al., 2001; Fonio et al., 2009; Benjamini et al., 2011).

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For the tracking and analysis of rodent location, body contour and mobility, computer vision systems exist that observe animals in real time from an overhead infrared-sensitive video camera. A summary of home-cage testing systems based on computer vision and other sensor techniques was provided by Spruijt and de Visser (2006). For the analysis of more specific body postures and behavioural patterns, however, researchers still rely on human observation. However, manual annotation is labour intensive, error-prone and subject to bias as a consequence of individual interpretation. In contrast, automated annotation is repeatable, objective and consistent, and it saves time and effort.

Research in behaviour recognition from video mainly focuses on human activities. During the past decade, many methods have been proposed to recognise activities such as 'walking', 'waving' or 'punching' (Aggarwal and Ryoo, 2011). Rodents do not have rigid limbs that make behaviours look different and, hence, easier to distinguish; the behaviours that interest biologists and neurologists can be very subtle. There is not a clear difference in animal posture or movement intensity between 'eating' and 'grooming snout' or between 'drinking' and 'sniffing the drink nipple'. Moreover, because rodents are nocturnal animals, their behaviour is preferably studied under dimmed or infrared light. This means that the automated system cannot use colour information, which is an important cue in human tracking. Conversely, there are many difficulties in human activity recognition that are not present in animal lab recordings; cameras and backgrounds are static and stable, and occlusions can be avoided.

In the literature, a few systems have been described that can automatically recognise animal behaviours that are more complex than locomotion and pose. For instance, Dankert et al. (2009) used action detection in the recognition of aggression and courtship behaviour of insects. For rodents, Rousseau et al. (2000) were the first to show that the detection of specific behaviours was possible. They applied neural network techniques to recognise 9 solitary rat behaviours from body shape and position, recorded from the side-view. The behaviour of 63.7% of the frames was correctly recognised compared to human-annotated ground truth. In 2005, Dollár et al. (2005) recognised mouse behaviour from the classification of sparse spatio-temporal features, reaching an accuracy of 72%. Steele et al. (2007) used alterations in home-cage behaviour for detecting perturbations in neural circuit function based on pose estimation. In 2010, Jhuang et al. (2010) predicted mouse strain type with an accuracy of 90% by comparing the relative frequencies of eight automatically detected behaviours. The features that they used were generated based on a computational model of motion processing in the human brain, followed by classification using a Hidden Markov Model Support Vector Machine (SVMHMM). They achieved an overlap between the generated 8-class behaviour annotation and human-annotated ground truth of 77.3%. This is a considerable result that is on par with human annotation, which had a measured agreement of only 71.6% according to the same article. Poor inter-observer agreement is a well-known problem reported by List et al. (2005), among others, who also addressed the difficulties of performance evaluation when the ground truth is ambiguous. Recently, Burgos-Artizzu et al. (2012) created a system for the recognition of the social behaviour of mice, from both top and side views; this system included the solitary behaviours 'clean', 'drink', 'eat', 'up' and 'walk'. Their approach was based on spatio-temporal and trajectory features and was extended with a temporal context model. They calculated the performance not as the percentage agreement over all video frames, but they instead took the average recognition rate per behaviour to account for the imbalance in behaviour frequencies. The average recognition rate over 13 behaviour classes was 61%. They measured a human inter-observer agreement of 70%. The authors remarked that human disagreement was associated almost entirely with the labelling of 'other' behaviours, whereas the automatic approach made more mistakes discerning among the specified behaviours. Removing 'other' from their performance measurement resulted in a human recognition rate of 91% and an automated recognition rate of 66%.

All of these systems show that, in principle, it is possible to recognise rodent behaviour from video footage however, the current systems have limitations. Most importantly, for all of the systems, changes in experimental setup, such as cage layout and position or camera distance and resolution, require re-training the classification algorithms. Some behaviours are restricted to location either due to the small cage or by definition. For example, for Jhuang et al. (2010), eating behaviour could only be detected close to the feeder. However, rodents often take pieces of food to eat elsewhere in the cage. It cannot be excluded that the classification relies on location for these behaviours, as location is part of the features in these systems. The second limitation is that not everything can be observed from the side view. Although the side view provides a better perspective for some behaviour bouts, other episodes where the animal is facing away from the camera are difficult to observe, and even the manually annotated ground truth has to be estimated from uncertain clues. Finally, there is a risk in training a behavioural system using a Hidden Markov Model, in which the state transition probabilities are learned from the training sequence. For drug-treated animals, the behavioural transition probabilities are likely to be altered. These changed transitions are a result of the experiment, not part of the model, and researchers will want to analyse the altered transition data.

A common feature of all of the studies mentioned above is that training and testing videos are recorded in exactly the same setup. With the system presented here we take recognition a step further by generalizing the applicability to robust detection in videos with a setup not seen before by the algorithm. The variations in setup concern the animal size, strain, camera distance, illumination, cage layout and cage background.

The structure of the paper is as follows. In Section 2, we describe the technical aspects of the proposed automated behaviour recognition (ABR) system, followed by a description of the two-way validation. First, we perform a straightforward frame-by-frame comparison of ABR with frame-accurate manual annotation. We evaluate videos recorded in the same setup as the training videos as well as on videos recorded in a different setup. Second, we perform an experimental study to validate ABR on a large set of without the need to supply frame-accurate manual annotation. For this we compared drug treatment effects detected by ABR to those detected by human observation. Rats are treated with two types of psychopharmaca that are well-known for their effects on behaviour: a stimulant drug (Amphetamine) and a sedative drug (Diazepam). Pharmacological validation is achieved by analysing the type and direction of the drug effects detected by both methods, as well as a comparison of the behaviour frequencies and durations across 5-min intervals. The results of the two validation methods are in Section 3. We present the study conclusions in Sections 4 and 5.

2. Materials and methods

2.1. Rat behaviour recognition system

In this study, image processing, machine learning and pattern recognition techniques are combined to create a system for automated behaviour recognition in rats. The ABR system can categorise video data into behaviours: 'drink', 'eat', 'groom', 'jump', 'rear-unsupported' (standing on hind legs), 'rear-wall' (standing on hind legs with front paws leaning against the wall), 'rest', 'twitch', 'sniff' and 'walk'. These are the categories that are currently annotated by hand in neurobehavioural research protocols and from which