Biometric Patterns in Long-Evans Rats for Automatic Behavior Analysis

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***Abstract*—Consistently detecting individuals is a key technical component of observing both wild and laboratory animal behavior. We present a dataset of hood patterns for Long-Evans laboratory rats in order to assess how well these patterns can be used as biometric markers to determine a rat's unique identity from video data. The database consists of 60 individual rats taken from 100 videos of pairwise interaction. The data is analyzed with several standard pattern recognition tools to test if building a recognition database based on hood pattern is feasible. Preliminary results are encouraging but leave room for obvious improvement. A reliable recognition module based on hood patterns would be an extremely useful tool in automation, since it can run in parallel to other approaches to tracking and identity maintenance and either increase accuracy or provide an independent ID check for automatic quality control in fully automated systems.**

Keywords—Long-Evans rats, Hooded Norway rats, long-term tracking, Dataset, Animal Biometrics, Individual recognition.

Fig. 1: Example of different individuals from the dataset showing the variation in lighting, size, and coloration. These images were taken from video sequences in a consistent pose, walking forward, that clearly shows the hood pattern.

I. Introduction

Long-term, minimally invasive, behavior analysis of animals has long been a goal in the research community. The reason is twofold; first, this type of automation allows for a more scalable, quicker and cost-effective analysis of traditional video data. Second, it allows entirely novel types of analysis due to the novel scale duration and finer quantitative resolution of individual actions. For example, high resolution pose estimates could uncover previously unknown social cues in animals. For single animals and simple interactions excellent tools already exist, however, social interactions between multiple individuals over longer periods of time still present significant challenges and is an active area of research [1], [2], [3].

Maintaining the identity of individual animals is one of the fundamental difficulties in this type analysis since differences in behavioral state or tendencies toward certain actions are only useful if observations at one time can be reliably linked to a specific individual. In practice, this problem is often posed as a tracking problem and solved via visual appearance or motion models to maintain identity between video frames and/or by adding identifying visual or radio frequency markers. In this paper we investigate the use of patterns in coloration of laboratory rats (*Rattus norvegicus*) of the Long-Evans strain as a biometric marker akin to fingerprints in humans. This strain has a distinctive "hood" pattern and is commonly used in behavioral cognitive studies, [4], [5], [6], see Fig. 1. In such studies consistent identity of multiple interacting individuals where interactions can lead to confusion are particularly interesting.

The presented approach is related to the re-identification problem in visual tracking, but poses a slightly more general question about the identification quality of the markers themselves, i.e. if the coloration is a biometric marker [7]. To be a good biometric marker, patterns should be uniquely identifying between many individual rats taken in different times and conditions. Biometric markers would make any type of long term observation more reliable, as they could be used either directly for analyzing individual images, for re-identification during tracking, or could be used in parallel to tracking methods in order to check the long-term identity maintenance of tracking software. This complementary approach could be particularly useful in completely automated settings where independent identity measurements could be used for quality assurance.

To answer the question of feasibility as a maker, we present a dataset of 60 individual rats interacting in pairs, see Section III, and give some initial results assessing the quality as a biometric marker, see Section IV. The concluding Section V discusses directions for future research.

II. Related Work

Given raw video data, the task of automated behavior annotation has several challenging steps. Individuals need to be detected, tracked, and analyzed. The detection problem is to find instances in a video frame or image; the tracking problem is to associate detected instances in multiple video frames and to associate them; These tracked video data are the basis for quantitative behavior analysis, such as [8]. Production grade open-source and commercial products exist for behavioral analysis in many different animal, e.g. CTrax [9]

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Noldus [10], [3] and often combine detection, tracking, and analysis modules.

Animals with uniform appearance, shape, and where social interactions do not produce overlapping locations are much easier to track than highly deformable ones. For example, there has been considerable success in tracking and analyzing large volumes of fruit fly interactions [9].

For highly deformable and closely interacting animals, like rodents, current tools work well for analyzing behavior of single animals or social interactions where there is no risk of confusion. Existing long-term trackers used on socially interacting rodents, use visual markers [2], or a combination of strong segmentation algorithms (to help maintain identity) together with other traits, such as heat signatures [11] or learned appearance models [12].

The closely related recognition problem is to identify individuals from a database of known individuals. Biometric studies in animals often focus on wildlife observation, where fully tracking the motion of individuals is not feasible [7], [13]. In these applications, single video frames and photos need to be matched to specific individuals.

Here we investigate the same problem for back patterns of Long-Evans rats. A reliable biometric, that does not require any additional instrumentation, would be an invaluable addition to any existing visual analysis toolkit. It could be used as either as a direct tool for data association during tracking or as a complementary system to check and correct other tracking software, e.g. [11] which uses the heat signature recorded with a thermal camera to correct data association when the tracker has low confidence.

Recognition is extensively studied in the pattern recognition literature and human biometrics community. Biometrics in humans requires insight into the particular features, e.g. key-points in human faces or minutiae in fingerprints. We suspect that the hood pattern should be a good biometric and compare several pattern recognition approaches for recognizing individuals: 1) using the outline of the hood pattern and applying a generic shape recognition algorithm [14], 2) appearance based methods in pixel space [15], [16] and 3) feature-based method [17]. We apply these generic pattern recognition tools to our novel rat biometric dataset described in the next section.

III. DATASET

The dataset was generated from video data of two rats socially interacting in a 29"x29" square arena, with relatively even lighting conditions and a light background, though variations within videos and across the field of view exist, see Fig. 1. These videos were collected for a separate experiment investigating the neurobiology of social interactions. The procedures for data collection were approved by the Institutional Animal Care and Use Committee at the researchs' home institution.

The rats were observed by an overhead camera (*Camera description*: color CCD MicrVideo camera. 1/3" CCD, 600 TV lines, 0.0001 Lux, 3.6mm lens: 1.18"x1.18" square). The individual images were selected via two criteria based on the rat body curvature and on the frame view: 1) the rat's body should be stretched and 2) it should be possible to see the entire hood pattern from a single view. For example, Fig.2 depicts four viewpoints for a given rat. In the leftmost image, the rat is bent; in the second and in the third images, despite the rats are stretched, it is not possible to see the entire hood. Only the rightmost view obeys both criteria.

We used a semi-automated approach to scan through large amounts of video data and then selected frames that might fulfill both criteria (view point and curvature), but had many false positives. After thresholding, we used four measures to automaticaly localize and crop the rat in each frame: 1) *Area*: the number of pixels inside the rat outline should be lesser than the sum of the area of the two rats. This way, we avoid selecting images where the rats are intarecting, probably touching each other. 2) *Solidity*: the ratio between the outline area and the area of its convex hull (threshold > 0.7). 3) *Aspect ratio:* the ratio between width and height of the rat (threshold < 0.3). 4) *Angle:* the angle formed by topmost, centroid and bottommost points should be greater than $178°$. These sets contained frames that generally fulfilled the stretching criteria, from which the frames with a complete view were picked manually.

The selected images were rotated such that the head of the animals were directed upwards. Then, the images were cropped to 120x50 pixels, centered at the rat's center of mass. Furthermore, the animal's tail was not kept on the resulting image since it was marked with an artificial mark (black Sharpie) and therefore must not be used as a phenotypic characteristic.

Fig. 2: Curvature/Viewpoint-based selection criteria. Example of different viewpoints for a given rat. Only the rightmost right obeys the selection criteria.

The proposed rat biometric dataset contains images of 60 Long-Evans rats. In which, for each animal we selected 5 images, resulting in a dataset composed of 300 images. Additionally, we created a testing dataset of 290 images which were collected from the same set of cropped that we select the dataset samples. The Fig. 1 portrays the variation in size, coloration and lighting of samples in the dataset.

IV. PRELIMINARY RESULTS AND FUTURE WORK

Since the irregular outline of the dark hood is the most striking visual feature, one approach is to make use of the shape of the hood as a biometric marker. Alternatively one could compare samples directly in pixel space and feature space. Since those seem reasonable approaches to solve the recognition problem, we present results for all of them. They work but leave room for improvement. Likely a combination of using shape for alignment and using graduation in coloring as a component of computing the match score will be the most effective.

For matching by outline we used a shape matching technique [14] which works by first finding an outline for the shape by detecting the edge between the dark hood and light colored body. The matching algorithm then find globally discriminate points selected along the contour and solves the correspondence problem between points in two distinct shapes. The similarity between samples is computed by estimating an aligning transform between them. The cost for this transformation and the distance between corresponding points are used together as the measure of similarity.

For feature-based method, we used Affine-SIFT (ASIFT) [17]. ASIFT is an extension of SIFT, which itself is invariant to translation, rotation, and scaling. However, ASIFT is also fully affine invariant. It simulates a set of sample views of the original image by modifying two camera axis orientation parameters (latitude and longitude angles), then applies SIFT to the new set of views.

For the appearance based method, we consider the following two quality metrics: structure similarity and feature similarity.

Structure similarity (SSIM)[15] is used for measuring the similarity between two images. The principal idea is that human visual system is highly sensitive to the structural distortions and automatically compensates for nonstructural distortions (a change of luminance or brightness, a change of contrast and a spatial shift). It assumes that the original image signals have strong neighbor dependencies which are carrying important information about the structures of the object. This method compares local patterns of pixel intensities that have been normalized for luminance and contrast.

Similar to SSIM, feature similarity (FSIM) [16] is also proposed to measure image quality according to salient low-level features: phase congruency (PC) and gradient magnitude (GM). PC is a contrast-invariant and dimensionless measure of the significance of a local structure, and GM is computed as the secondary feature to encode contrast information. PC and GM are complementary and they reflect different aspects of the HVS colorspace in assessing the local quality of the input image.

A. Preliminary Results

Each testing image was compared with all the images in the dataset using shape matching technique [14], SSIM [15], FSIM [16] and ASIFT [17]. For the shape matching technique, the rat with minimum cost is considered as the correct ID; for SSIM and FSIM, we consider the rat with the highest value as the correct ID; and for ASIFT we measured the transition tilt, which quantifies the deformation from an image to another.

Table I shows the accuracy of the four methods. It shows that shape matching and ASIFT methods are more reliable than appearance based method though shape matching only uses an outline of the hood pattern. Especially, it is difficult to identify two rats with a similar hood pattern using purely appearance-based method (Fig .3).

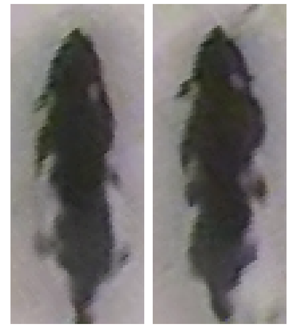

Fig. 3: Different rats with a similar pattern

TABLE I: Accuracy for the four methods used

Method	Accuracy
ASIFT	75.5%
Shape Matching	74.1%
SSIM	57.6%
FSIM	54.8%

In Table II, the second column represents that the accuracy of ASIFT and SSIM among the images that misidentified by shape matching method, and similar for third and fourth column. From Table II, we can see there are 54.6% and 24.0% of images that misidentified by shape matching but ASIFT and SSIM can give correct results. Similarly, for ASIFT and SSIM.

Regarding Shape Matching and ASIFT, since around half of the misidentified images can be classified correctly by the other method, the information obtained by them are slightly different. Therefore, combining shape recognition algorithm and feature based algorithm may be one of our future work for rat identification.

TABLE II: Accuracy of each method in misidentified images

Method	Shape Matching	ASIFT	SSIM
Shape Matching	none	49.2%	52.8%
ASIFT	54.6%	none	49.6%
SSIM	24.0%	14.1%	none

Fig. 4 gives five representative images from testing dataset. (a) to (c) are examples that are misidentified by all the methods in Table I, and (d) and (e) are identified correctly by all the methods. The main differences between (a), (b), (c) and (d), (e) are: 1) (d) and (e) have more changeable outline patterns, for example, (d) has prominent edge pattern, and (e) has zigzaging edges, which are easier to be distinguished by used methods. However, (a) and (b) have smoother outlines; 2) even if (c) has slightly irregular ourlines, it is blurred.

B. Future Work

To be useful the recognition software needs to be coupled with an automated way to gather samples from an input video. While the detection, quality assessment, and cropping are

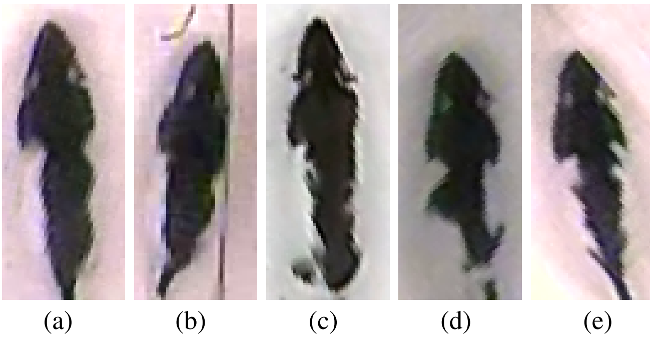

Fig. 4: Representative testing images showing both exapmles of individuals that were difficult to identify (a)–(c) and easy to identify (d)(e).

partially automated at this point, we plan to fully automate the process in the future.

Relatedly, since most video frames do not capture the rat's entire back pattern (see Fig. 2), for future work, we plan to augment the dataset with side view for each rat, which will provide additional information that could promote more efficient and reliable re-identification approaches. Alternatively, multiple frames could be fused together to provide a synthesized view of the complete pattern. This is similar to current trends in human face biometrics that use 3D reference models to account for appearance variations in 2D images.

In addition to using geometric reasoning to produce better 2D appearances of the patterns, we plan to use 3D cameras that can help with viewing patterns as well as providing more information about the animal's pose. Such additional 3D sensors can also simplify and improve the detection, segmentation, and tracking directly compared to a purely visual approach.

An improved biometrics pipeline might also enable behavior observations in laboratory animals where reliable tracking is unfeasible, for example, long term observations that only have a heavily occluded lateral views, such as filming housing cages.

V. Conclusion

We present a new data set for testing the biometric quality of Long-Evans hood patterns. Preliminary results using off-the-shelf pattern recognition pipelines without tuning suggest that this approach should be possible in populations with many animals. Extracting the shape outline first and using it as a representation works better than comparing the appearance in pixel space directly. This is likely due to an alignment issue. Therefore, a combined approach or reference model based approach may provide even greater accuracy.

A biometric rat recognition pipeline would be helpful to creating reliable, long-term, automated, behavior analysis system. As such, we expect a refined version of this work to be a useful tool for researchers working with this type of animal.

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