Computing a Rodent's Diary

Rana Farah, J.M. Pierre Langlois, Guillaume-Alexandre Bilodeau

Abstract — Rodent monitoring in biomedical laboratories is a time consuming and tedious task. Several automatic solutions that rely on different types of sensors have been proposed. Computer vision provides a significantly more universal and less intrusive solution. In this article we propose a new method to detect and classify three behaviors in rodents: Exploring, Rearing, and Static. The method uses Motion History Images and a Multiple Classifier System to detect the three behaviors under typical laboratory conditions. It is independent of the color of the rodent and of the background. The method performs equally well on short and long video sequences, achieving a success rate of 87%.

Key Words: Computer vision, behavior identification, lab animals, rodents, motion history image, SVM, classification.

I. Introduction

Animal models are powerful and proven approaches to perform research in the health sciences. In such a model, animals are used to test drugs to verify their applicability for human treatment or to study diseases, such as epilepsy. Rodents are particularly useful animals because of their physiology's similarity to that of humans. Rodents make up more than 90 percent of animals used for medical research [1]. In a typical experiment, a rodent is monitored over a period of hours, days or weeks for specific states and behaviors. Animal monitoring is time consuming and tedious. Experimenters must devote a significant portion of time monitoring and classifying rodent behavior. Biomedical laboratories would benefit from automated, quantitative monitoring devices. These devices would allow for longer observation time leading to more accurate results and conclusions. Several solutions that rely on traditional sensors such as pressure, vibration and infrared beams have been in use. These are reported in [2] and [3] and in industrial systems such as IntelliCage of NewBehavior [4]. However, these systems are limited in the type of information that they can supply and they cannot detect complex behaviors. For instance, light or vibration sensors are limited to general motion and tracking without the ability to identify the nature of the motion. Moreover, these systems are costly, require maintenance, and may be intrusive. Computer vision presents a promising alternative that is non-intrusive, relatively cheap and mostly universal in the sense that it has the potential to detect and classify complex behaviors which presently require several sensor types.

Rodent monitoring presents great challenges. Rodents are kept in cages that are stacked on shelves, and this constrains camera localization. In a biomedical laboratory, the illumination is seldom uniform. Cages are host to all sorts of reflections due to their material, and their floors are covered with textured and deformable bedding to ensure animal comfort. The contrast between the animal's color and its surrounding color can be limited. Finally, the rodent's shape is extremely deformable, making modeling its body a difficult task.

In this paper, we propose a method for detecting and classifying three behaviors for rodents in a typical biomedical environment. The three behaviors are:

Exploring: the rodent is moving around its environment or it is exhibiting actions such as sniffing or sensing with its whiskers.

Rearing: the rodent is in an elevated position with its front paws above the ground.

Static: the rodent is motionless. This may be due to the rat resting, sleeping or being motionless as part of a seizure behavior.

These three behaviors were chosen among a list of medium-level behaviors that are of interest to our partners at Sainte-Justine Hospital, to measure the effect of certain diseases or drugs on the physical or mental state of rodents. Other researchers have also focused on these behaviors. For instance, Rudenko et al. [5] measured the number of rearing instances and the distance travelled by R6/2 mice suffering from Huntington's disease to observe their hypoactivity patterns. Gibbs et al. [6], in a study of long-term consequences of prolonged febrile seizures, identified arrest of movement or freezing as one of the manifestation of seizure in rats.

The proposed method uses the size of a rodent's Motion History Image (MHI), its centroid position and the output of a Multiple Classifier System (MCS) to detect and classify exploring, rearing and static. The MCS combines the outputs of two support vector machines (SVMs). The first SVM classifier uses the normalized height of the rodent's MHI as feature. The second SVM classifier uses the Histograms of Gradients (HOG) of the rodent's MHI. The contributions of this paper consist of a new method to use MHI features to detect and classify animal behavior, and a new rule to combine the output of the two SVM classifiers. The rule is based on dynamic instantaneous weights.

The paper is organized as follows. Section II describes related work on animal behavior detection. Section III provides background on MHI and MCSs, and Section IV motivates our approach. Section V describes the proposed methodology, while Section VI describes the classifier training methodology, the datasets and the experimental results. Section VII concludes the paper.

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This work is funded by CRSNG (Conseil de recherche en science naturelles et en génie du Canada) and the FQRNT (The fonds de recherche du Québec – Nature et technologies).

II. Related work

Several projects in the litterature are specialized in animal behavior detection. This is justified by the large difference in anatomy and behavior between humans and animals. Rodents have few distinguishable features, their limbs are almost unnoticeable and some of them exibit brisk motion [7].

Nie et al. [8] used a computer vision technique to detect and classify rat behaviour in forced swim tests. The method detects immobility, climbing and swimming. A combination of binarization, frame differencing, centroid calculation and filtering is used to monitor a dark mouse in a transparent container filled with water and positioned above an IR illuminator. The same authors [9] used a combination of frame binarization, frame differencing, centroid calculation, edge and contour extraction and a filtering method they developed in [10], to detect six behaviors in mice. These included moving, rearing, immobility, head grooming, left-side scratching and right side scratching. These approaches require the use of a High Frame Rate camera.

Dollar et al. [11] used 3D spatio-temporal features that rely on gradients in addition to a k-means classifier to detect drinking, eating, exploring, grooming and sleeping behaviors. Jhuang et al. [12] also used 3D spatio-temporal features. They combined them with ten other position and velocity based features as well as a Hidden Markov Support Vector Machine to detect eight behaviors: eating, drinking, grooming, hanging, micro-moving, rearing, resting, and walking. The method was tested on long video sequences to demonstrate its stability. However, it requires background subtraction as a prerequisite.

Commercial solutions have also been provided for rodent monitoring. We are aware of only one that exploits computer vision. CleverSys [14] identifies 21 different behaviors. However, the system relies on background subtraction, and, for efficient results, requires the use of a special system that provides adapted lighting and a uniform white background [16].

All of the above methods use binarization or background subtraction to isolate the rodent before identifying its behavior. This adds constraints on the environmental settings and on some parameters of the ongoing biomedical experiment. For instance, due to the binarization, a high contrast is needed between the animal and its background for the method to be efficient. In fact, two of these methods [11] [12] are applied only on dark mice. In addition, with the exception of the works by Jhuang et al. and of Wilk et al., these methods have not been proven for long video sequences [12].

III. Background and Motivation

A. Motion History Image

The MHI is robust in suppressing static objects in the scene and is able to preserve short duration complex movements [17]. These characteristics are crucial for rodent monitoring, because these animals tend to exhibit erratic and, in some cases, abrupt motion. This type of motion occurs for example when rodents are grooming, or when they are having seizures. MHI is also invariant to target color [17] and to background color. This is important because rodents have different colors and are constantly subject to color distribution variations. The color distribution of the rat changes when illumination is not uniform and when it is crossing from one illumination zone to another. Color distribution change is also caused by the constant deformation of the rodent's body as it moves around.

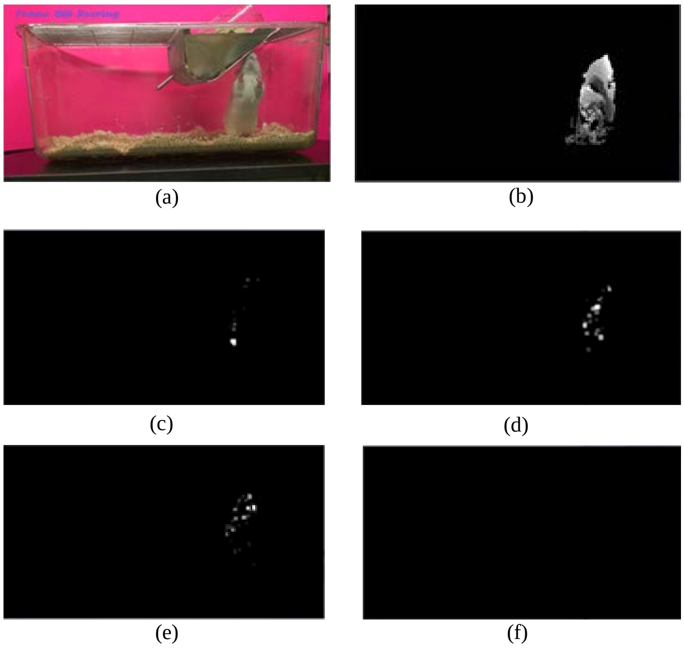


Fig. 1: Two methods for computing the MHI of the frames leading to the frame in (a), (b) using frame differencing, (c-d) using optical flow [18]. (c) MHI_x^+, (d) MHI_x^-, (e) MHI_y^+, (f) MHI_y^-

MHI is a map that represents the presence of motion at different instances in time [18]. Every pixel in the MHI represents motion imprint at that pixel. Bright and dark pixels represent recent and older motion, respectively. Bobick and Davis [19] were the first to use MHI to recognize actions or behaviors. The authors used an image differencing technique to compute the motion pixels in order to update the MHI. They also used the seven Hu moments [21] and the Mahalanobis distance [22] to describe the MHI and classify the behavior. The authors later used background subtraction instead of image differencing to decrease noise in the resulting MHI [23]. Ahad et al. [24] argued that image differencing and background subtraction do not produce suitable MHIs. The image differencing method leaves holes in the MHI and background subtraction is not always efficient [24]. Instead, they used optical flow, the seven Hu moments and the k-nearest neighbors algorithm to construct, describe and classify the MHI, respectively. The original MHI presents a self-occlusion problem [24]. When an action presents two motions going in opposite directions, the later part will occlude the earlier. Ahad et al. [24] proposed a method with four MHIs to solve this problem. Each MHI represents a direction of the motion. The optical flow was used to calculate the MHIs.

When applying the optical flow based MHI on video sequences of rodents, the information provided is not sufficient. Fig. 1(b) shows an MHI computed using frame differencing on a video sequence of a rat. Fig.1 (c-f) shows the four MHIs computed using the optical flow as in Ahad's et al.'s article [18] on the same consecutive frames. The difference between the quantity of motion pixels displayed in Fig. 1(b) and in Fig. 1 (c-f) is substantial. Fig. 1(b)

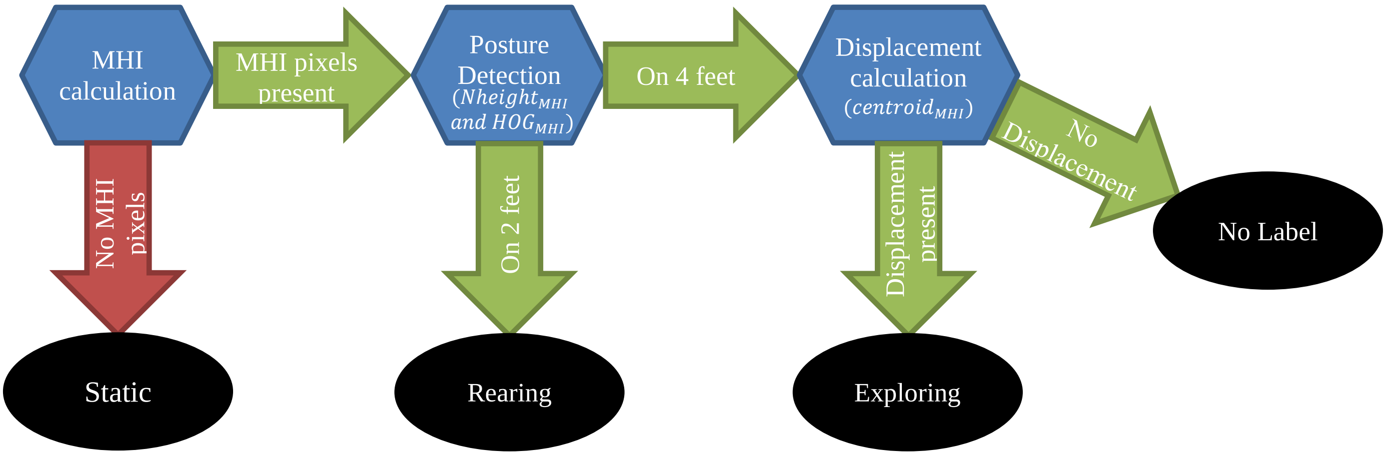


Fig. 2: The strategy used to detect and distiguish the three behaviours

contains more information about the motion of the rodent than the other figures. Fig. 1(f), which represents the negative motion in the y direction, contains no motion pixels. These results are explained by the fact that the rodent's body is extremely deformable. This makes its texture very variable and hard to model. Rodents also tend to have less texture with respect to their environment. This excludes optical flow features from being formed or maintained on the rodent's body [25] and disadvantages any method that uses optical flow on rodents [11].

The exploring, rearing, and static behaviors of rodents are not prone to self-occlusion, as addressed in [18], given that these actions are one-directional. However, self-occlusion can still be caused by the fact that the body of the rodent is not shaped in rigid parts that move together maintaining the same dimensions. This may cause the motion of one part of the rodent to occlude the motion of another. This problem is addressed in Section IV (B).

B. Multiple Classifier Systems

In an MCS, the outputs of several base classifiers are combined to estimate the class of a given object. MCSs are often adopted for their ability to simplify the combination of several features. MCSs are also known for their performance, which exceeds that of individual classifiers in the best case [26]. In the worst case, their performance is similar to the best classifier's [27]. When several features are considered, these features are combined into one longer feature. The numerical values of each feature are normalized to the range [0,1] to give equal weight to each one [28]. It is also possible to weigh each feature differently [29]. Appropriate weight selection can be a tedious and complex process to achieve the right balance. In this work, we set the MCS to take advantage of the strongest feature at each instance of its usage.

Several authors have studied and compared MCSs. Kunchva et al. [28] separated MCSs in two categories: classifier selection and classifier fusion. Classifier selection rules are based on the assumption that each of the base classifiers is an expert in a local area of the feature. When a feature is presented whose value is in a certain local area, the output of the corresponding classifier is advantaged over the others. Fusion classifier rules are used with the assumption that all classifiers are experts in the whole feature space and some fusion rule is used to combine their outputs. Zhang and Duin [30] further separated the fusion MCSs into homogeneous and heterogeneous classifiers. Homogeneous classifiers consist of the same classifier that is trained with different sets of data, whereas, heterogeneous classifiers consist of different classifiers that are trained with the same dataset. Zhang and Duin also categorized the fusion-based MCSs into fixed and trainable combiners. Fixed MCSs combiners consist of combiners such as maximum, mean, and majority voting, while trainable combiners consider the output of each of the base classifiers as a new meta-feature. Any classification algorithm could be used to estimate the final class [28] [30]. Finally, the rule choice should be based on the nature of the data and the classifiers involved. After analyzing and discussing ten different combination rules, Duin et al. concluded that there is no universally efficient rule [31].

In this paper, we propose a simple fusion rule that combines the output of SVM classifiers. This particular fusion rule is used for its simplicity and ease of applicability in this case. It was also chosen for its ability to allow instant dynamic weights that favor the strongest output in a given instance under the assumption that the strongest output is the most accurate.

IV. Proposed Methodology

We now describe the method used to detect and classify the exploring, rearing and static behaviors in rodents.

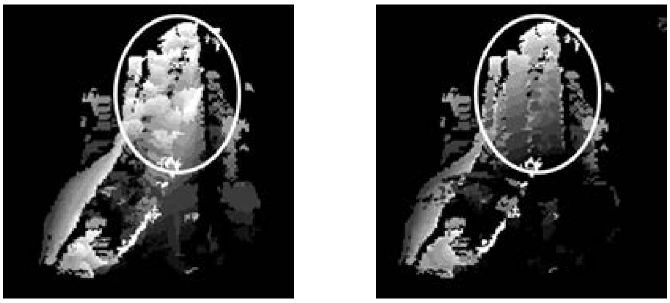
A. Strategy

The proposed strategy is illustrated in Fig. 2. First, the MHI of the sequence is computed. When there are no MHI pixels, then the rodent is assumed to be in the static state. Otherwise, an MCS is used to determine the posture of the rodent. If the classifier returns an "on two feet" verdict, then the rodent is assumed to be in the rearing state. If the rodent is classified as "on four feet" and a displacement exists, then the rodent is assumed to be in the exploring state. A displacement is calculated as a displacement of the centroid of the MHI by a distance that is 10% of its size in the x- or the y-dimension. If the displacement is less than 10%, then the behavior is not labeled.

B. Motion History Image:

The MHI is computed for each frame as described in [19] with modifications to avoid self-motion occlusion. The MHI is computed in five steps:

a) A decay factor is imposed on the MHI $H_\tau(t-1)$ computed at $t-1$ as shown in (1):



(a) (b)

Fig. 3: Difference between (a) the MHI method proposed by Bobick and Davis et al.[19] and (b) the method described in this paper.

$$H_\tau(x,y,t) = max\{H_\tau(x,y,t-1) - \delta,\ 0\}, \quad (1)$$

where $H_\tau(x,y,t)$ is the MHI value at time t at coordinates x and y, and δ is the decay parameter.

b) The motion presence map $D'(x,y,t)$ at time t is calculated as in [19] by subtracting two consecutive frames.

c) The MHI is updated according to the motion presence map $D'(x,y,t)$. In the original method [19], the MHI is updated by setting the value at the coordinates x and y to τ if the corresponding value in $D'(x,y,t)$ is greater than zero as in (2).

$$H_\tau(x,y,t) = \begin{cases} \tau & if\ D'(x,y,t) > 0 \\ H_\tau(x,y,t-1) & otherwise \end{cases}, \quad (2)$$

where τ is the duration of the action. The duration of the action corresponds to the number of frames used to construct the MHI. However, this method is prone to MHI self-occlusion as stated in [18]. To avoid self-occlusion, we modify (2) so that the MHI at time t and coordinates x, y is updated only if its value is equal to zero. This is shown in equation (3).

$$H_\tau(x,y,t) = \begin{cases} \tau \times D'(x,y,t) & if\ H_\tau(x,y,t-1) = 0 \\ H_\tau(x,y,t-1) & otherwise \end{cases}, \quad (3)$$

Fig. 3 shows the difference between the two methods. Fig. 3 (a) shows the MHI using Bobick and Davis' original method and Fig. 3 (b) shows the method described in this paper. The ellipses indicate the region where self-occlusion reduction is most apparent. In Fig 3 (a), the bright colors are dominant and they cover large regions. This is the manifestation of self-occlusion as bright colors represent recent motion and are covering the traces left by older motion. While in Fig 3 (b) self-occlusion is reduced and the history of the movement is more apparent by the gradual change in color from dark (old motion) to bright (recent motion).

d) Small motion blobs are considered as noise and are eliminated from the frame. These blobs are generated by reflections on the cage and motion from the cage floor bedding.

e) The largest blob in the MHI frame is chosen to represent the rodent. We assume that the rodent is the only dynamic entity in the scene and most likely to be the one generating the largest blob.

C. Features

Two features were considered to detect the three targeted behaviors: the normalized height of the MHI and the Histogram of Gradients of the MHI.

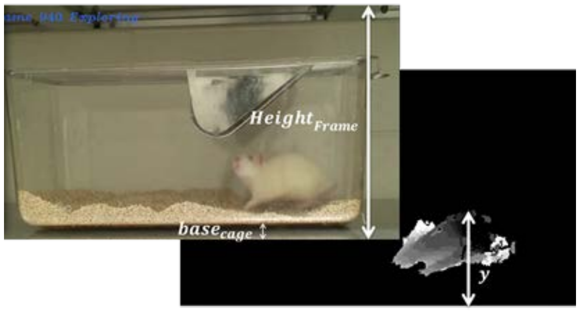


Fig. 4: Parameters used to calculate the normalized MHI height

In this paper, the MHI's normalized height ($Nheight_{MHI}$) is defined as the y-coordinate of the highest point in the MHI. The MHI's height is normalized to account for the dimension variation in each rodent. $Nheight_{MHI}$, is calculated as follows:

$$Nheight_{MHI} = \frac{y - base_{cage}}{length_{animal}}, \quad (4)$$

Where y is the y-coordinate of the highest MHI pixel that belongs to the rodent and the $base_{cage}$ is the lowest pixel that belongs to the floor of the cage in the frame. $length_{animal}$ is the largest length recorded for the animal in the given video. It is measured when the rodent is crossing the cage. This is when the maximum length usually occurs. This parameter could be substituted by the actual animal length or height if measurements were taken before the experiment. Fig. 4 shows the different measurements used.

$Nheight_{MHI}$ is considered as a feature because height is a very strong indicator of the posture of the rodent. In fact, when the MHI is high the rodent is probably on two feet and consequently in a rearing state. Fig. 5 shows the height distribution of $Nheight_{MHI}$ calculated with respect to two postures (on two feet, on four feet) using a training set. $Nheight_{MHI}$ can be used to achieve some level of discrimination between the two postures, but it is not sufficient given that the two distributions are not completely separated.

Histograms of gradients (HOG) [32] are considered due to their ability to model texture. The MHI texture is a strong indicator of certain behaviors. Fig. 6 shows a rat that rises on two feet, going down on four feet and walking. We can distinguish the various strata patterns that every action imprints on an MHI. For instance, in Fig. 6 (a), we can distinguish, on the right side of the frame, the ascending

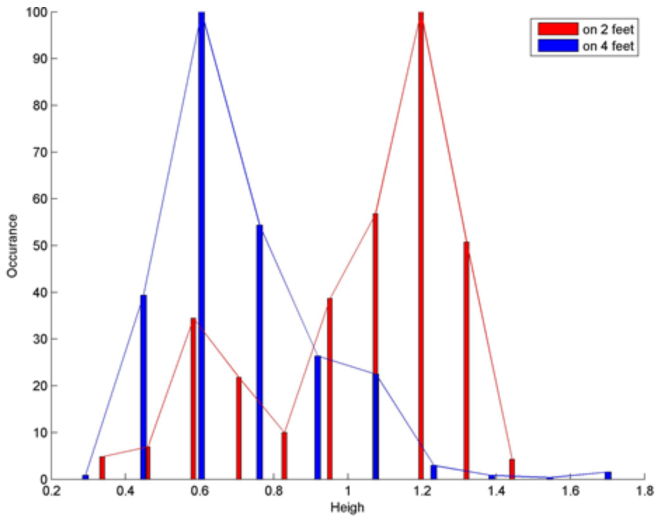
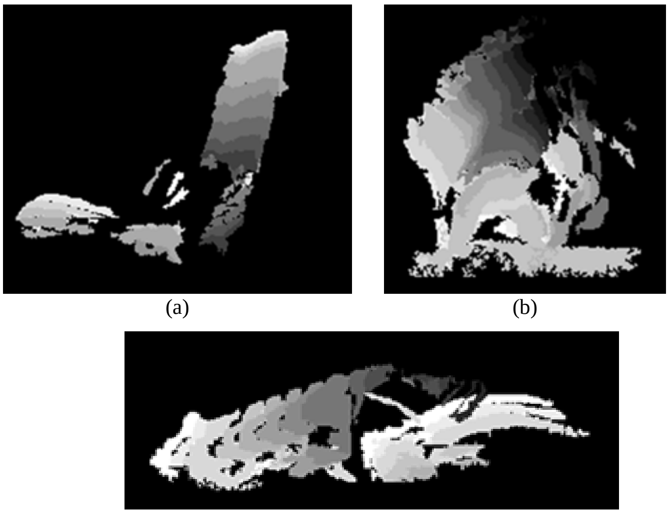


Fig. 5: Height distribution



(a) (b) (c)

Fig. 6: MHI representing diferent types of motion, a) a rat getting on two feet, b) a rat going down on 4 feet, c) rat walking

pattern that marks the discretized stages when rising occurs. The color changes from dark at the bottom, to mark older motion, to bright at the top to mark newer motion. On the left side of the frame, the motion of the rat's tail produces the same pattern.

The HOG are computed as described in [25] on the rodent MHI blob. The HOG algorithm described in [25] considers ROIs with variable dimensions, where the grids have fixed dimensions and the cells have dynamic dimensions. This is useful because the MHI is continuously changing dimensions. The dimension of the grid is 4×4. Nine bins are used as suggested by the author of the original article [32], which results in an 144-value feature.

D. Multiple Classifier System

We propose the following fusion rule for the MCS:

$$R_{MCS}^t = W_1^t \times D_1^t + W_2^t \times D_2^t + \cdots + W_n^t \times D_n^t, \quad (5)$$

The weights W_n^t at each instant t are calculated in such a way as to strengthen the contributions of the strong base decisions (D_n^t) to the response of the MCS at t. In other words, for each decision instance t, the weight attributed to each base classifier is proportional to the certitude of the decision of that base classifier at that instance t. This rule is simple and allows a higher weight for the assumed most accurate base classifier at each instant.

Our MCS uses two base classifiers: the first classifier (SVM_{ht}) is an SVM that classifies $Nheight_{MHI}$.The second classifier (SVM_{HOG}) is an SVM that classifies the HOG of the MHI.

To calculate the posture at instant t based on the responses ($R_{SVM_{ht}}^t$,$R_{SVM_{HOG}}^t$) of the SVM classifiers, two thresholds ($vt_{SVM_{ht}}$, $vt_{SVM_{HOG}}$) are used. We define the base classifier estimation (D_n^t) as the difference:

$$D_n^t = R_n^t - vt_n, \quad (6)$$

At each instant t, to interpret the response of the n^{th} two-class classifier, we consider the value of D_n^t. Given that each class is assigned a scalar value, if D_n^t is negative, then the posture belongs to the class with the low value. Otherwise, if D_n^t is positive then the posture belongs to the high value class. In addition, we assume that the further the response R_n^t of a base classifier is from its corresponding calculated threshold vt_n, the more assertive its decision D_n^t is. Consequently, we calculate the instant weight attributed to each base classifier as the absolute value of its decision.

In this case, the fusion rule to determine the posture at each instant (frame) becomes:

$$R_{MCS}^t = W_{ht} \times D_{SVM_{ht}}^t + W_{HOG} \times D_{SVM_{HOG}}^t,$$

Where,

$$W_{ht} = \left|R_{SVM_{ht}}^t - vt_{SVM_{ht}}\right|, \quad (8)$$

$$D_{SVM_{ht}}^t = R_{SVM_{ht}}^t - \mathrm{vt}_{SVM_{ht}}, \quad (9)$$

$$W_{HOG} = \left|R_{SVM_{HOG}}^t - \mathrm{vt}_{SVM_{HOG}}\right|, \quad (10)$$

and

$$D_{SVM_{HOG}}^t = R_{SVM_{HOG}}^t - \mathrm{vt}_{SVM_{HOG}}, \quad (11)$$

The posture is evaluated as

$$posture = \begin{cases} on\ two\ feet & if\ R_{MCS} < 0 \\ on\ four\ feet & otherwise \end{cases}, \quad (12)$$

where $posture$ is the final decision of the MCS.

We used the OpenCV libraries for the implementation of the SVM classifiers [33].

V. Classifier training, data Sets and results

In this section we detail the parameters of the MCS used. We also describe the datasets used for training the system and the sequences used to for testing and evaluation. Finally, we present experimental results.

A. Training datasets for the classifier

The training dataset samples were extracted from three different video sequences of a single rat in a cage. The three video sequences where chosen to represent different background colors. We recorded the sequences in a medical laboratory where experiments aiming to study seizures in rats are conducted. The cages were transparent, stored on shelves and covered with beddings. The illumination was provided by fluorescent lamps fixed to the ceiling. The camera was mounted in such a manner as not to disturb the ongoing experiments. One cage with one rat was recorded at a time. The rats in the video sequences are all white. The background colors used are pink and white (the natural colors of the wall behind the cage).

Brute force iteration are used to determine the threshold (vt_n) associated with each base classifier. The value of vt_n is varied at each iteration. The threshold vt_n is set as the value that minimizes the number of false decisions for that particular classifier using the training dataset.

B. Test sequences for the algorithm

We tested the proposed methodology on four different video sequences of rats and mice, listed in Table I. These four sequences are different from the sequences used for training. The first three sequences showcase different white rats in cages. These sequences were recorded under the same conditions as the training dataset. The last sequence was extracted from the dataset provided in [13]. It is a sequence of a black mouse in a cage. The cage is transparent and its floor is covered with bedding.

(a)

	exploring	rearing	static
exploring	0.94	0.04	0.00
rearing	0.11	0.89	0.00
static	0.00	0.00	1.00

(b)

	exploring	rearing	static
exploring	0.80	0.14	0.00
rearing	0.39	0.57	0.03
static	0.00	0.00	1.00

(c)

	exploring	rearing	static
exploring	0.93	0.02	0.01
rearing	0.08	0.90	0.02
static	0.00	0.00	1.00

(d)

	exploring	rearing	static
exploring	0.78	0.06	0.02
rearing	0.13	0.84	0.02
static	0.16	0.00	0.84

Fig. 7: Confusion Matrices for a) Sequence 1, b) Sequence 2, c) Sequence 3, d) Sequence 4 [13]

TABLE I: TEST SEQUENCES

Sequence	Rodent	Rodent Color	Background Color	Number of frames
Sequence 1	Rat	White	Pink	6770
Sequence 2	Rat	White	Pink	17881
Sequence 3	Rat	White	Scene Colors	7072
Sequence 4 [13]	Mouse	Black	Scene Colors	68227

C. Experimental settings and results

During the experiments, the decay factor δ (equation (1)) was set to 1 as in most of the state of the art. We examined our training dataset, and calculated that a rodent stays a minimum of 0.22 seconds on two feet. This minimum time is equivalent of 13 frames given that the videos are recorded at 60 fps. Accordingly, the action duration parameter τ (equation (3)) was empirically set to 13. This shortest standing duration was adopted because it was enough to account for a rearing behavior. It also ensures that two consecutive actions do not occlude each other.

TABLE II: KERNEL TEST RESULTS

	Percentage of false classifications	
	Linear kernel	RBF kernel
SVM_{height}	6%	10%
SVM_{HOG}	23%	20%

A linear kernel was used for SVM_{height}, and a radial basis function kernel was used for SVM_{HOG}. These choices are based on the experimental results shown in Table II. The linear and the Radial Basis Function (RBF) kernels were applied to SVM_{height} and SVM_{height}. Sample sequences extracted from the training dataset were used to calculate the percentage of false classifications for every kernel and for every feature. These samples are different from the samples initially extracted to train the classifiers. Table II shows that SVM_{height} performed better with the linear kernel, while SVM_{HOG} performed better with the RBF kernel.

Several snapshots of the labeled sequences are shown in Fig. 8.

To evaluate the results objectively, we calculated the confusion matrix for each sequence and the average of the resulting four confusion matrices. The sequences were evaluated with respect to a ground truth built by us. We manually labeled all the frames of each sequence. This was done by indicating the first frame and the last frame of every instance of a behavior of interest, and labelling each frame in between with the same labels. The results for the four sequences are summarized in Fig. 7.

Rearing was less accurately estimated due to the fact that when a rodent is in a rearing position, it can stay motionless for some time. However, the rodent usually still exhibits some motion in its lower body due to the motion of the tail or some fidgeting around its posterior feet. This results in an MHI that covers only the lower part of the body of the rodent. In this case, the MHI has a small height and is classified as on 4 feet.

Even though the static behavior was perfectly identified for the first three sequences, the decrease in sequence 4 is due to the low resolution of the video. The low resolution prevents the morphological operations to reduce the noise

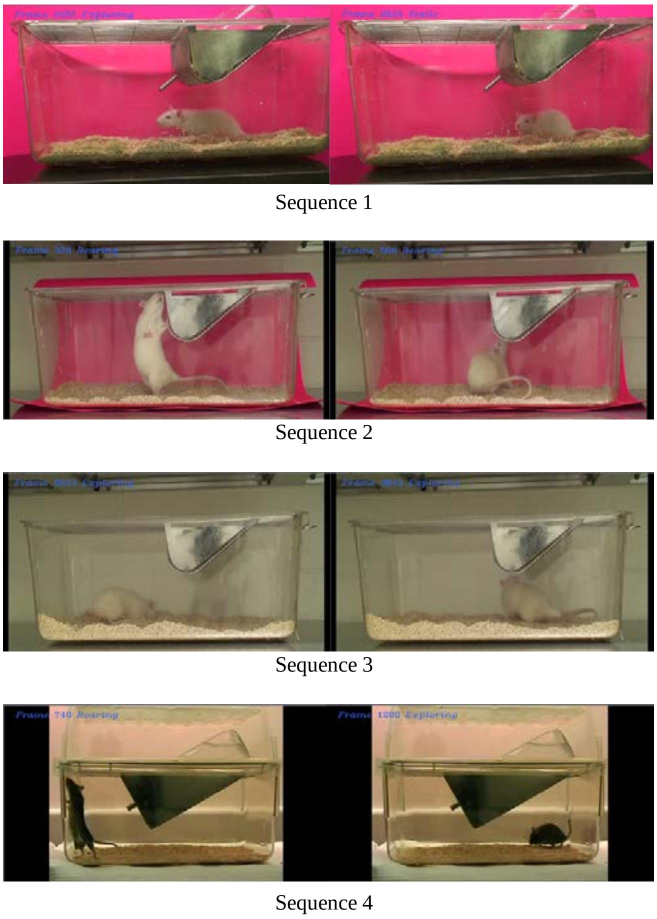


Fig. 8: Snapshots from the test sequences showing different behaviors

without suppressing the MHI of the mouse. Occasionally, the largest MHI blob was associated with noise and not the mouse itself, thus when the rodent was actually static some erroneous activity was detected.

The results suggest that our method is robust to various environmental conditions. For example, the white rats were monitored while the background was also white, decreasing the contrast between the rodent and the background. Furthermore, the illumination was not controlled or uniformly distributed in the region of interest.

The training set only included white rats, but the test set included white rats and black mice. The fact that MHI is insensitive to color is seen as the reason why the results for test sequence 4 are nonetheless quite good.

VI. Conclusion

In this paper, we proposed a method to detect and classify three rodent behaviors: exploring, rearing and static. The method uses MHI-based features with a Multiple Classifier System where at each instance the base classifier with the strongest decision is advantaged. The method was tested under typical biomedical lab conditions, in such a way as not to disturb ongoing experiments.

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