A Monitoring System of a Hamster Based on Video Image Analysis

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Abstract

This paper proposes a monitoring system for a hamster that uses a video camera. The proposed system first processes the video image taken from the top of the cage, and then extracts features related to posture information and internal state. These features are used to discriminate between daily activities and other activities. This allows the system to alert when the hamster behaves differently from its daily routine. We analyzed the daily behavior of a hamster by using the proposed system. The results showed that the behaviors of a hamster changed when stimuli are given from outside the cage, and the system could discriminate them appropriately.

Keywords: abnormal detection, rodents, video camera, monitoring system, behavior tracking, heart rate variability

1. Introduction

As COVID-19 has been rampant, the number of pets has increased [1][2]. Therefore, it is helpful for pet owners if they can continuously monitor their pets. Conventional behavioral analyses of living things include visual observation of behavioral changes associated with changes in the living environment [3][4]. However, it is difficult to quantify the results, as the evaluation varies from researcher to researcher.

During the development of new drugs, research has been conducted to create behavioral models by measuring the movements of laboratory mice with a camera [5][6]. However, this method is not suitable for detecting behaviors that are not performed in daily life because it aims to quantify specific behaviors. Even though, there is a system to measure heartbeat and behavior by using a sensor module that includes a heart rate sensor, it is not suitable for measuring daily activities because the stress caused by such devices attached to a body changes its state [7].

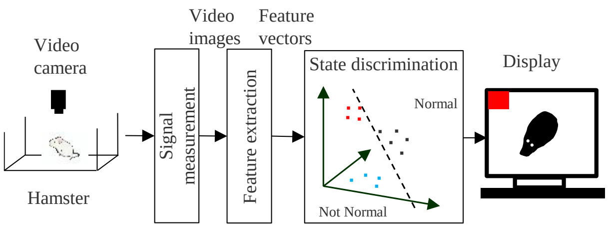

Fig. 1. Structure of the proposed system.

This paper proposes a monitoring system for pets based on video image analysis. The system can discriminate their state by extracting their internal information, which does not appear in their behavior, and its behavioral information simultaneously from a video camera. The proposed system extracts the heart rate variability from the heartbeats of the animals. In apartment buildings, other pets may also be kept, which can cause a great deal of stress [8]. The proposed system can detect states that do not appear in behavior by extracting the heart rate variability. In addition, the proposed system can alert when an unusual state is detected, and the owner can check the surrounding information from the video image, which may help in the early detection of injuries.

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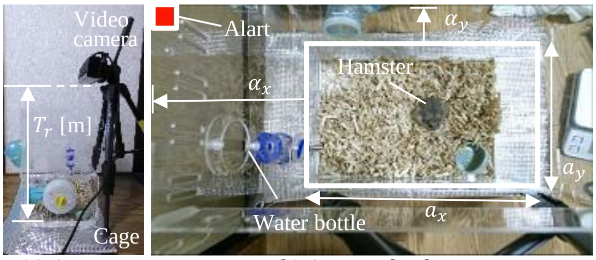

(a) Setup (b) System display

Fig. 2 Overview of the proposed system.

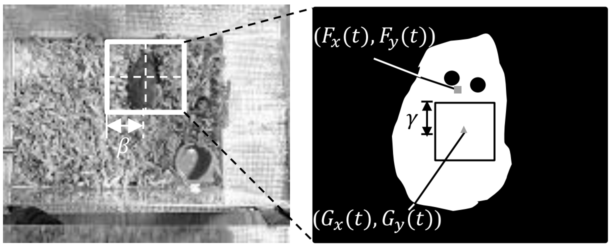

Fig. 3. Video image processing.

2. Method

In the proposed system, a video camera (Kinect V2, Microsoft) is used for real-time monitoring of a hamster in a cage, and alerts the owner when the system detects a state different from its daily behavior. Figure 1 shows the structure of the proposed system. The system consists of three parts: 1) signal measurement, 2) feature extraction, 3) state discrimination, and 4) display to present the information to the owner.

2.1 Signal measurement

The measurement environment of the system is shown in Fig. 2(a). A video camera is set up parallel to the ground without any tilt above a typical cage (T_r m), so that the daily life of a hamster can be measured. Various equipment such as a water bottle is placed (see Fig. 2(b)), and the height of the camera T_r is adjusted to maximize the hamster's view angle as much as possible.

In the signal measurement, the video image measured from the video camera is imported into the PC at a sampling frequency of f_s Hz. As shown in Fig. 3, a $a_x \times a_y$ rectangular area A with margins α_x and α_y pixels in each axis direction of the measurement area (see Fig. 2) is set from each frame to omit the living environment in the cage. The features for state discrimination were then extracted through the following signal processing.

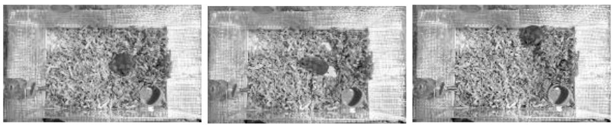
(a) t = 31.8 [s] (b) t =121.2 [s] (c) t = 300.0 [s]

Fig. 4 Scenes from the experiment.

After the measurement image is converted to the HSV color system, threshold values (the maximum and minimum for each component: $h_{\mathrm{th}}^{\max}$, $h_{\mathrm{th}}^{\min}$, $s_{\mathrm{th}}^{\max}$, $s_{\mathrm{th}}^{\min}$, $v_{\mathrm{th}}^{\max}$, and $v_{\mathrm{th}}^{\min}$) are set to extract only the hamster area, and the binary image is generated, where white (0) represents the hamster and black (1) represents the other area (see Fig. 3).

The body center coordinates of the hamster $G_x(t)$, $G_y(t)$ are obtained by calculating the center of gravity of the region of the pixels with value (0). A square region B with perimeter β pixels from $[G_x(t), G_y(t)]^{\mathrm{T}}$ is then defined, and positions estimating the hamster's eyes are also extracted as set threshold values. The coordinates of the center of gravity of the pixels in B with value (0) assuming the position of the eyes is tracked as the position of the hamster's head $[F_x(t), F_y(t)]^{\mathrm{T}}$ (see Fig. 3).

In addition, to measure heart rate variability as internal body information, a square region C of γ pixels around $[G_x(t), G_y(t)]^{\mathrm{T}}$ (the position of the hamster) in region A is defined, and the average value $H(t)$of the green component in region C is calculated.

2.2 Feature extraction

To extract the features that represent the motion and internal body information of the hamster, in this section, the change in the center of gravity $m(t)$, the change in body shape $[r(t), \theta(t)]$, and the heart rate information $h(t)$ is calculated.

2.2.1 Movement information

The change in body shape is defined using the hamster's center of gravity $[G_x(t), G_y(t)]^{\mathrm{T}}$ and head position $[F_x(t), F_y(t)]^{\mathrm{T}}$ as the features representing the hamster's body shape, referring to the method of Yuman *et al.*[4]. In this study, the tail of a rat, which is also a rodent, is used; however, it is difficult to obtain the tail of a hamster; therefore, in this paper, the following new equation is used for calculation.

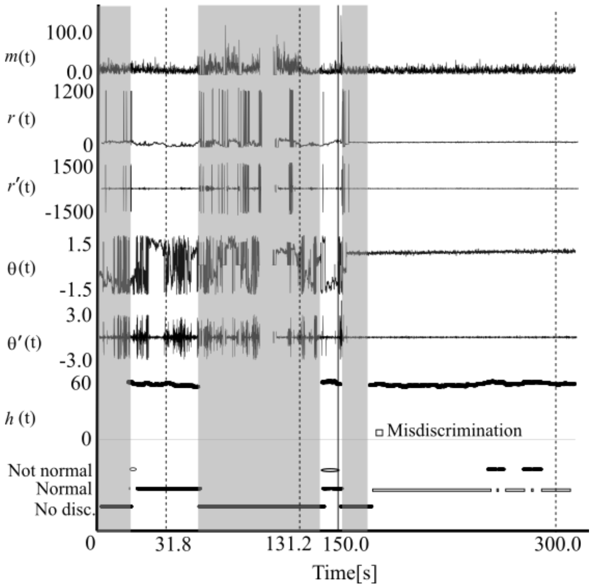

Fig. 5. Experimental result.

$$r(t) = \sqrt{\left(G_x(t) - F_x(t)\right)^2 + \left(G_x(t) - F_x(t)\right)^2} \quad (1)$$
$$\theta(t) = \tan^{-1}((G_y(t) - F_y(t))/G_x(t) - F_x(t))$$

where $r(t)$ is the distance between the head and the center of gravity of the hamster, and the larger the value, the more stretched the body. $\theta(t)$ is the angle between the center of gravity and the head. The value indicates the direction of the hamster, with clockwise being positive.

2.2.2 Internal body information

The heart rate information $h(t)$ is extracted from the heart rate during t_{H} s as a feature representing the internal state of the hamster. Tsumura *et al.* [9] improved the accuracy of heart rate information extraction by applying a band-pass filter to video images measured by five cameras and then performing independent component analysis. Here, because it is sufficient to calculate the heart rate, the peak is detected from $H(t)$, and the inverse of the time difference is multiplied by t_H. A second-order digital Butterworth filter with a cutoff frequency of $(f_{\mathrm{l}}, f_{\mathrm{h}})$ was applied to $h(t)$ to detect the peak easier. The mountain-climbing method was applied after applying a band-pass filter.

2.3 State discrimination

Threshold discrimination is used to classify the state of the hamster. First, the threshold value is determined based on the training data $\boldsymbol{Z}^n = [z_1(t)^n, \dots, z_d(t)^n]^{\mathrm{T}}$ $(n = 1,2, \dots, N)$, obtained by measuring and extracting features of scenes containing K types of daily activities. The classification result $s(t)$ can be obtained by inputting a new feature vector. At this time, $s(t)$ becomes $s(t) = 1$ when the behavior is judged to be in the normal state (when values for all dimensions exceed the threshold), and $s(t) = 0$ when a state different from daily activity is obtained.

Table I. Confusion matrix.

	True	False
Positive	789	1975
Negative	110	90

2.4 Display

In this section, the results of the system are presented on the display to inform the owner of the hamster's state. When the state of the hamster is different from that of daily life ($s(t) = 1$), the area of $s_x \times s_y$ pixels in the upper left corner of the system screen is displayed in red, as shown in Fig. 3.

As described above, the state of hamster daily can be monitored with the system and notify the owner of any abnormalities. In addition, because the owner can check the video images around that time, he/she can visually understand the situation.

3. Experiment

To verify the effectiveness of the proposed system, the daily activities of the hamster was monitored using the system.

3.1 Experimental conditions

The experiment was conducted in the rearing environment shown in Fig. 1($T_r = 0.5$ m), with the cabin removed so that the hamster's movements could be observed. We tried to reduce the stress of the hamster by matching the measurement environment and the rearing environment as much as possible. To distinguish their daily conditions, the data were measured in the evening, when nocturnal hamster started their activities. In the experiment, we generated a sound by clapping hands after 150.0 s in the measurement of approximately 5 min. (4838 frame, $f_s = 16.16 \pm 0.38$ Hz) to add load to the hamster. In addition, inter-frame difference of $[r(t),$ $\theta(t)]$ is calculated and used to discrimination $[r'(t),$

$\theta'(t)]$ ($\boldsymbol{Z}^n = [m(t)^n, r'(t)^n, \theta'(t)^n, h(t)^n]^{\mathrm{T}}$). Threshold values for discrimination were set as $-10 \le m \le 10$, $-20 \le r \le 20$, $-0.5 \le \theta \le 0.5$, $63 \le h$.

The other parameters were set by trial and error, and $\alpha_x = 680$ pixels, $\alpha_y = 150$ pixels, $a_x = 990$ pixels, $a_y = 650$ pixels, $\gamma = 21$ pixels, $s_x = s_y = 100$ pixels, $h_{\mathrm{th}}^{\max} = 95$, $h_{\mathrm{th}}^{\min} = 60$, $s_{\mathrm{th}}^{\max} = 30$, $s_{\mathrm{th}}^{\min} = 0$, $v_{\mathrm{th}}^{\max} = 75$, $v_{\mathrm{th}}^{\min} = 125$ for hamster's position estimation, and $h_{\mathrm{th}}^{\max} = 65$, $h_{\mathrm{th}}^{\min} = 30$, $s_{\mathrm{th}}^{\max} = 100$, $s_{\mathrm{th}}^{\min} = 50$, $v_{\mathrm{th}}^{\max} = 40$, $v_{\mathrm{th}}^{\min} = 10$ for eye position estimation. In addition, f_{l}= 4.76 Hz f_{h}=7.14 Hz is set because the heart rate of hamster was 280-412 bpm [10].

3.2 Results and discussion

Figure 4 shows the experimental scenes, and Figure 5 shows the results. The horizontal axis represents the time, and the vertical axis represents, from the top, the change in center of gravity $m(t)$, the change in body shape [$r(t)$, $\theta(t)$], their inter-frame difference [$r'(t)$, $\theta'(t)$], and heart rate information $h(t)$, and the result $s(t)$. In the section where the center of gravity could not be traced owing to the hamster being hidden under straw, no discrimination is made (shaded area in fig 5). From figure 4, it can be seen that 31.8 s and 121.2 s show a large change in the value of $\theta(t)$. These are the areas where the hamster moves such as curling up, and the system can track the hamster's behavior.

After 150.0 s (vertical line in Fig. 5), the extracted features fluctuated due to the sound. The results for the condition before the sound are also shown in Table I. Table I shows the confusion matrix for the state before and after the sound. Here, the state after the sound was considered to be a state different from daily life.

From these results, the proposed system can be used for the daily monitoring of a hamster. However, because only one example is shown in this paper, we will increase the measurement time and perform real-time monitoring for 24 h.

4. Conclusion

This paper proposes a monitoring system for a hamster using a video camera. The system can discriminate between different states from daily life by extracting features appearing in the behavior and internal states. In the experiment, the daily life of a hamster was monitored using the proposed system, and the change was evaluated in behavior before and after the sound was generated. Although the average discrimination rate was low (average discrimination rate: 30%), the system showed the possibility of immediately informing the owner of a situation where the hamster was overloaded.

In the future, we will conduct real-time monitoring for an extended period, and consider feature extraction and classifier to improve discrimination accuracy.

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