A Human Fall Detection System Using an Omni-Directional Camera in Practical Environments for Health Care Applications

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Abstract

This paper proposes a vision-based fall detection system for the elderly and patients at home or in health-care institutions. The system uses an omni-directional camera to avoid blind spot. The system also considers practical environmental factors that may take place in our daily life, such as the occurrence of light source glimmer, turning a light on and off and leaving over static abandoned objects in the environment. We divide the fall down patterns in omni-directional images into non-radial and radial directions according to the angle associated with a body line. We further categorize the radial fall down patterns into inward and outward directions. The recognition features proposed for the system include angle and length variation associated with the body line and motion history images. Given these features, a simple thresholding and decision tree technique is adopted for fall detection. Experimental results show that the proposed system can solve the problems of light source glimmer and static abandoned objects. In fall-down detection, the recognition accuracy is 0.87 and the Kappa value is 0.75. These results show that the proposed fall down detection system is quite effective.

1 Introduction

This paper presents a vision-based fall down detection approach to be used in a home health-care system. The view of a traditional camera is limited such that usually more than three cameras are needed to cover the entire surveillance area. However, multiple cameras require more effort to set up and control, and they also need additional algorithms to find the corresponding relationships among the images from different cameras. Therefore, this paper employs just one omni-directional camera (map cam) instead of using multiple cameras to avoid these problems. Some researchers used a map cam to do fall detection in the past [1]-[6]. But they only considered highly ideal and simplified environment for their work. Therefore, this paper presents a fall detection system for more realistic environment in our daily life [7] [8], such as turning a light on and off and leaving over static abandoned objects and resulting in multiple targets in the environment. In addition, this paper further probes into different fall down modes in omni-directional images to improve the recognition performance of the previous work and enhance practicability in a real-world environment. The proposed fall detection system is particularly useful to senior citizens living alone at home or with others at sanatoriums.

2 Method

This section describes the proposed fall detection system and addresses some related issues in a realistic environment.

2.1 Adaptive thresholding for light intensity

An adaptive thresholding technique for light intensity is proposed to detect the light source glimmer problem. First, the system subtracts the average intensity I_B of background from average intensity I_f of input images to obtain the level of light source glimmer effect I_{diff} :

$$I_{diff} = I_f - I_B \tag{1}$$

Next, add a fixed camera thresholding noise n_s to the dynamic changing value obtained from Eq. (1) and get a correction threshold for image binarization:

$$threshold = n_s + I_{diff} \tag{2}$$

The level for n_s is chosen according to the camera used. Utilizing this method can effectively solve the source glimmer problem because a single fixed threshold may either lead to broken foreground (threshold is too high) or result in too much noise (threshold is too low). With adaptive thresholding, the system is less sensitive to light intensity variation, and thus improving the system's adaptivity to the environment with various lighting conditions.

2.2 Light on and off detection

Several image statistics are computed form the first N consecutive input images. Then for every new input frame, the statistics are recomputed or updated. The process continues until there is no more input image. For every group of N images, sample mean, variance, and standard deviation of pixel intensities are obtained. A light on and off detection scheme is shown in Figure 1. A status indicator w will be set to 1 when the sample standard deviation is greater than a predefined threshold, MaxSigma. This means the system can not work normally because the light intensity changes abruptly and the system is in an unstable state. Therefore, the system stops capturing the foreground and ceases to update the background. The w will be set to 0 when the sample standard deviation is smaller than another predefined threshold, MinSigma. This means the system can work normally and the light source is stable. In this case, the system can continue to capture the foreground and update the background.

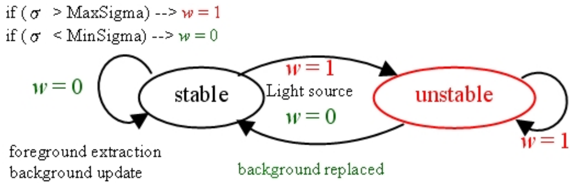

Figure 1. The state transition diagram for on and off light detection.

2.3 Detection and removal of static abandoned objects

Assume only one person is in the surveillance area, meaning that it could just have one moving object and the others are all static objects. We utilize this characteristic to detect static abandoned objects. First, compute the location difference between the ith object center at current time t, $C(i,t)$, and the ith object center at previous time $t-1$, $C(i,t-1)$. When the difference is smaller than a predefined threshold η_1 (more specifically, $\| C(i,t)-C(i,t-1)\| < \eta_1$), then a counter is incremented by one; otherwise the counter is not updated. Take every 30 frames as a counting interval. When the counter reading is greater than another predefined threshold η_2, then this object is considered a static object. The counter will be reset to zero later on and the counting process repeats for each counting interval.

Next, the static object detected will be blended into the background image and become part of the background. Therefore, when the system performs foreground detection next time, the static object will not appear in foreground, and the successful removal of the static abandoned object is achieved.

2.4 Fall detection

Two types of fall down from omni-directional images can be categorized by the angle θ between the body vector $\overrightarrow{IJ}$ and the reference vector $\overrightarrow{MI}$, as shown in Figure 2. A larger angle represents a non-radial fall, and a relatively smaller angle may indicate a radial fall (including radially inward and outward fall). The corresponding angle threshold for fall type detection is determined by the largest angle that can be obtained in normal walking conditions. Using the body line characteristic successfully detected the non-radial fall and radially outward fall [6], but it failed to detect radially inward fall. Therefore, we propose a tMHI (time Motion History Image) [9] [10] solution to solve this problem.

tMHI converts the foreground pixels in adjacent images by some time labels. It can record the object motion information within a period of time. Using tMHI can easily obtain the history information of continuous movement within a time period so that it can be used to analyze and recognize the motion behavior of a moving object. For the convenience of viewing and processing, we use Eq. (3) to normalize tHMI and obtain a gray scale image of b bits per pixel:

$$MHI^{i}_{gray}(x,y)=\begin{cases}\dfrac{tMHI^{i}(x,y)-(\tau-\delta)}{\delta}\times(2^{b}-1) & if\ tMHI^{i}>0\\ 0 & otherwise\end{cases} \qquad (3)$$

where τ denotes current frame or time, and δ is a user specified parameter that controls the recording length of motion information.

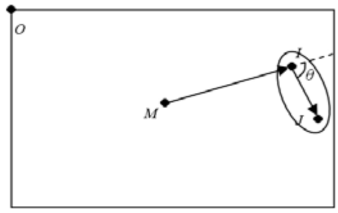

Figure 2. A schematic showing the body vector $\overrightarrow{IJ}$ and reference vector $\overrightarrow{MI}$ [6].

As shown in Figure 3, three distance measures (i_1, i_2 and i_3) are extracted as a feature for fall detection. A typical result of the feature is shown in Figure 4.

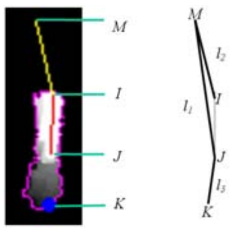

Figure 3. A schematic showing tMHI feature.

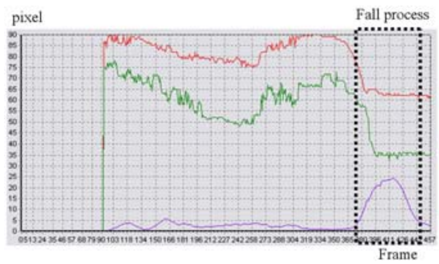

Figure 4. A typical result of tMHI-based feature when radially inward fall occurs.

A radially inward fall is detected if the following four conditions are must: (1) The standard deviation of $i_1 < \sigma_1$; (2) The standard deviation of $i_2 > \sigma_2$; (3) The standard deviation of object center displacement $< \sigma_3$; and (4) $i_3 > T$, where the first three predefined thresholds (σ_1, σ_2, and σ_3) are not sensitive to environment conditions and determined by experiments and the last threshold (T) may need minor adjustment for better performance.

Figure 5 gives the system flow chart of fall detection. Basically, it is a three-level decision mechanism for determining the fall-down type. The first decision is used to determine whether a non-radial fall occurs, and if not, it may be a radial fall. The radial fall is further divided into radially inward and outward falls. Although the features for radially outward fall cover part of the features for radially inward fall, the converse is not true. Thus, the second decision is used to determine radially inward fall. This decision order is better for overall recognition performance. The last decision is to determine whether we have a radially outward fall or not.

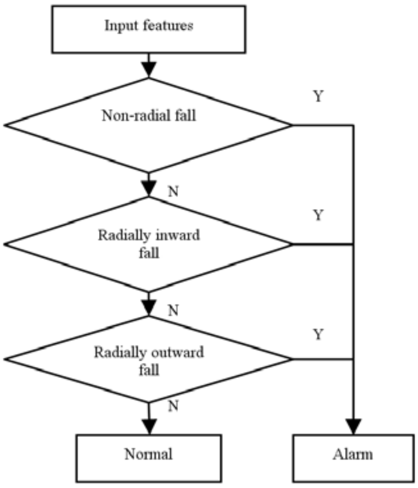

Figure 5. System flow chart.

3 Experimental Results and Discussions

3.1 Adaptive thresholding for light intensity

As shown in Figure 6, a single high threshold results in broken objects, and on the contrary a threshold that is too low will produce too much noise. With the adaptive thresholding technique discussed in Section 2.1, the foreground is extracted more successfully.

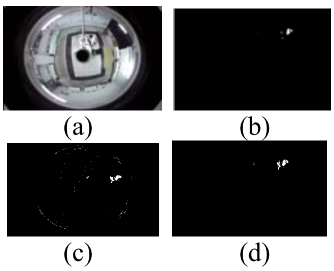

Figure 6. Binarization results using different thresholds: (a) Original image. (b) Noise threshold (fixed at 35). (c) Noise threshold (fixed at 20). (d) Noise threshold (fixed at 20) + I_{diff} (dynamic).

3.2 Light on and off detection

In this experiment, we simulate the behavior of turning the light on and off in our daily life. Part of light sources is turned off in the experiment. As shown in Figure 7, at Stage I, all lights are on; at Stage II, partial lights are turned off; at Stage III, there is no change in light condition; at Stage IV, all lights are turned on again; and at Stage V, there is no change in light condition.

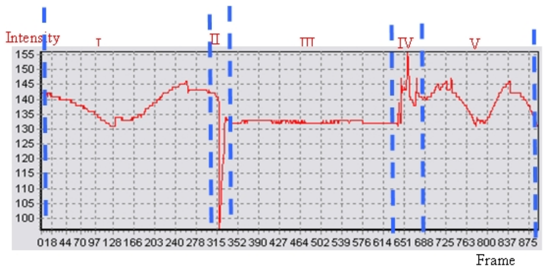

Figure 7. The average image intensity in light on and off experiment.

The experimental results are shown in Figure 8. The behavior of turning lights on and off can be detected successfully and the foreground can also be successfully extracted when there is no more abrupt change in light intensity.

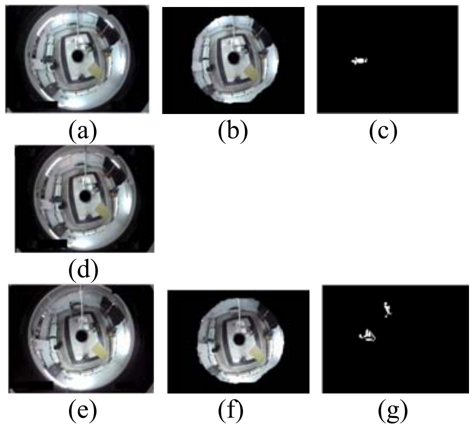

Figure 8. The experimental results in the case of turning partial light on and off. (a) Input image before light is off. (b) Background before light is off. (c) Foreground before light is off. (d) Input image at the instant of turning light off. (e) Input image after light is off. (f) Background after light is off. (g) Foreground after light is off.

3.3 Detection and removal of static abandoned objects

As shown in Figure 9, the person being taken care brings an object into the surveillance environment. The object is left behind while the person is walking. Thus, the system would detect two objects, where one of them is the walking person, and the other is the abandoned object. The abandoned object is removed successfully, as can be verified in Figure 9.

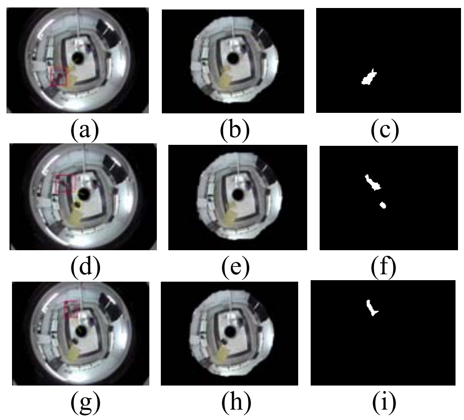

Figure 9. The experimental results of abandoned object detection and removal. (a) Input image before object is abandoned. (b) Background before object is abandoned. (c) Foreground before object is abandoned. (d) Input image after object is abandoned. (e) Background after object is abandoned. (f) Foreground after object is abandoned. (g) Input image after abandoned object is removed. (h) Background after abandoned object is removed. (i) Foreground after abandoned object is removed.

3.4 Fall detection

A total of 97 sets of the omni-directional image sequences are used in the simulation study. Those images contain many different situations of radial fall (32 of them are inward and 33 of them are outward) and non-radial fall (32 sets, including 5 from real situations discussed in Section 3). All 97 image sequences were processed for fall detection in the experiments and the performance is evaluated. The fall detection result is considered a success when the system recognizes a fall event (disregard the type of falling). A recognition error occurs when a normal walking person is classified as being falling. The experiment results are shown in Table 1. The system performance is evaluated and the result is shown in Table 2.

Table 1. Experiment result and comparison.

	Method proposed in this paper		Method proposed in [6]	
Fall accident / System judgment	True	False	True	False
Positive	86	13	67	21
Negative	11	84	30	76

Table 2. Performance evaluation and comparison.

	Method proposed in this paper	Method proposed in [6]
Accuracy	0.87	0.73
Sensitivity	0.88	0.69
Specificity	0.86	0.78
Kappa Value	0.75	0.47

The performance comparison shows that the system proposed here substantially increases the number of successful fall detection (from 67 to 86) and reduces the number of erroneous detection (from 30 to 11), as shown in Table 1. The accuracy is improved (from 0.73 to 0.87) and the Kappa value is increased significantly (from 0.47 to 0.75), as shown in Table 2. Therefore, this paper demonstrates an effective fall detection and recognition system.

4 Conclusions

The proposed system is aimed at the practical factors encountered in real environments for our daily life. Therefore, we attempt to solve the problems such as the occurrence of light source glimmer, turning a light on and off, and leaving over static abandoned objects. Experimental results show that the proposed system has overcome the practical environmental factors of light source glimmer and static abandoned objects. In fall-down detection, the recognition accuracy of the fall down system reaches 0.87 and the Kappa value [11] is up to 0.75. These results show that the proposed fall down detection system is quite effective.

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