Activity Recognition Based on Thermopile Imaging Array Sensor

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***Abstract* — In this paper, a low resolution infrared array sensor is used to develop an activity recognition system for elderly people. The sensor is composed of a 32x32 thermopile array with the corresponding 33° × 33° field of view. The outputs of the sensor are sequential images in which each pixel contains a temperature value. According to the thermopile images, the activity recognition system first determines whether the target is within the tracking area; if the target is within the tracking area, the location of the target will be detected and three kinds of activities will be identified.**

***Index Terms* — activity recognition, fall detection, thermopile imaging array sensor.**

I. INTRODUCTION

Nowadays, aging society becomes a major trend in most of countries around the world. According to the researches on aging society, although the increasing rate of population in the world is slowing down, the population aged 65 and over is increasing rapidly [1]. In addition, a large number of elderly people are living alone. To provide better care services to those elderly people, activity recognition and fall detection become more and more important for caregivers.

Generally, activity recognition is implemented by using wearable sensing devices. For example, sensors in smart phones [2,3], acceleration sensors [4,5], and capacitive sensors [6] have been used for activity recognitions. Researches show that the accuracy of the activity recognitions utilizing wearable sensing devices is high. However, the major limitation of wearable sensing devices is that the devices must be worn by elderly people, so there are stringent restrictions on the size and power consumption of the wearing detecting sensors. Using non-wearable sensing device can get rid of those restrictions and is friendlier to elderly people. Typically video cameras [7,8] and Doppler radar array [9] are employed to implement the non-wearable activity recognitions. However, the video-camera based methods may have issues of privacy invasions and the accuracy of the activity recognitions is poor in dark environments. Moreover, the system cost of the methods based on Doppler radar array is high [9].

In this paper, we have developed a non-wearable activity recognition system based on a thermopile imaging array sensor, HTPA32x32dR1L5.0/0.85F7.7eHiC, which is manufactured by Heimann Sensor GmbH [10]. The outputs of the sensor are thermopile images with a resolution of 32×32 pixels. The key advantages to use the thermopile imaging array sensor are: i) because the resolution of the sensor is much lower than that of video cameras, it almost has no issue of privacy invasion; and ii) because the sensor is designed to detect the infrared radiations, its performance is stable no matter in dark or bright environments. The activity recognition system developed by this paper recognizes the activities of the tracking target according to the following procedure: first, the system determines whether the tracking target is within the tracking area; if the target is within the tracking area, the location of the target will be detected and three kinds of activities will be identified.

The rest of the paper is organized as follows. Section II describes the setup of the activity recognition system and the measurement environments. Section III presents measurement results and discusses the results in details. Finally, concluding remarks are provided in Section IV.

II. SYSTEM SETUP AND MEASUREMENT ENVIRONMENTS

The information flow chart of the activity recognition system developed in this paper is shown in Fig. 1. According to the flow chart, first, a thermopile array sensor captures thermopile images with a resolution of 32×32 pixels and sends the images to a Raspberry Pi 3 through an I2C interface. Then the Raspberry Pi 3 calibrates the thermopile images and saves the calibrated images into an SD card. Finally, the images stored in the SD card are transferred to a PC and processed with MATLAB programs to determine the existence, the location, and the activities of the tracking target.

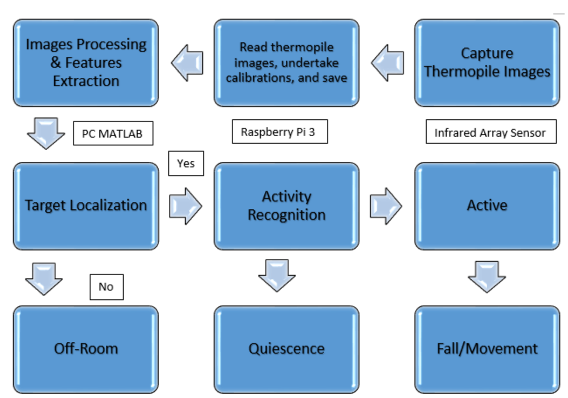

Fig. 1 Information flow chart of the activity recognition system.

Our experiment is set up in our laboratory, the area of which monitored by the thermopile imaging array sensor is 4 meters wide and 5.78 meters long. As shown in Fig 2, the sensor is installed on a wall at the height of 1.8m and overlooks the ground at an angle of 16.5° (i.e. half of 33 °) below a horizon line. Such installation allows the thermopile imaging array sensor observing more area below 1.8m for activity recognition.

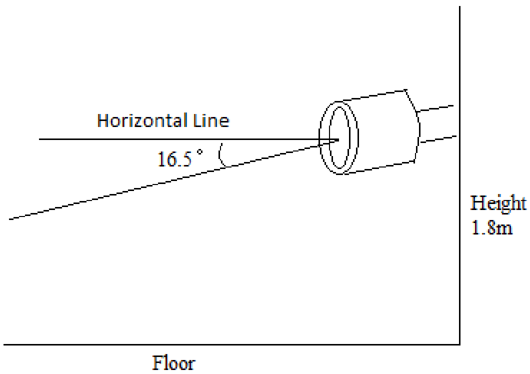

Fig. 2 The orientation of the sensor

III. Activity Recognition Algorithm and Measurement Results

A. Algorithm Explanation

As shown in Fig. 3, the activity recognition algorithm includes four steps: (1) image preprocessing; (2) connected domain extraction; (3) localization by feature point; (4) activity recognition. The details of the steps are explained in the following paragraphs.

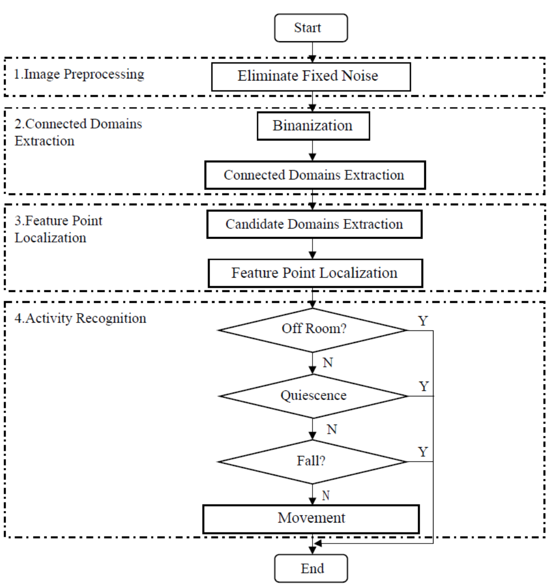

Fig. 3 Activity recognition algorithm of the proposed system

Step I: Image Preprocessing

The images captured by the thermopile imaging array sensor contain two kinds of noises: (1) Fixed noises, circled in black in Fig. 4, are some fixed temperature offsets existing in the same locations of every single frame. It is caused by the system errors during capturing and calibrating images. (2) Random noises, circled in red in Fig. 4, are temperature offsets that randomly appear in different locations of some frames.

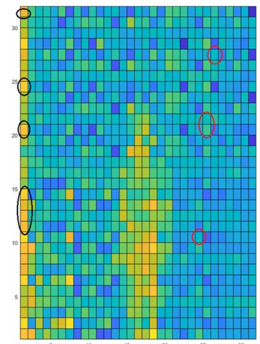

Fig. 4 Algorithm Effect Picture

In order to remove the fixed noises from the observing area, the background temperature should be subtracted from the original temperature. The process is demonstrated in the following equation (1, 2).

$$Z_p(n) = X_p(n) - Y_p(n) \tag{1}$$

$$Y_p(n) = \alpha Y_p(n-1) + (1-\alpha) X_p(n) \tag{2}$$

where $X_p(n)$ denotes the temperature of the pixel p ($P \in [1,1024]$) at the nth frame, $Y_p(n)$ represents the background temperature at the same frame, and $Z_p(n)$ stands for the output after preprocessing. A large number of experiments show that when α=0.99, most background noises can be removed. The results are shown in Fig. 5. Compared with Fig. 4, the fixed noise has been eliminated, but the random noise still exists.

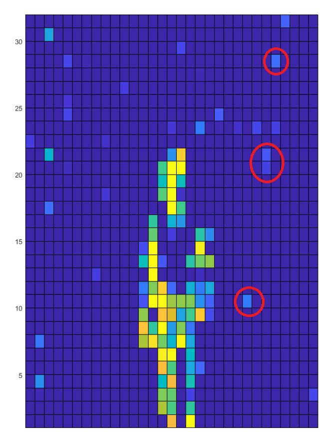

Fig. 5 Image after Eliminating Fixed Noises

Step II: Connected Domains Extraction

The connected domain extraction algorithm is developed to distinguish the connected domains caused by random noises from the one of target. This algorithm is used to scan an image and group its pixels into domains based on pixel connectivity.

The images obtained from step I are first converted to binary images. Then the 8-connectivity method is used for extracting connected domains $S_i(n)$ which represents the i^{th} connected domain in the n^{th} frame. As shown in Fig. 6, extraction results include not only the target circled in blue, but also the interfering connected domains due to random noise. Obviously, the connected domain of target contains more pixels than the interfering ones.

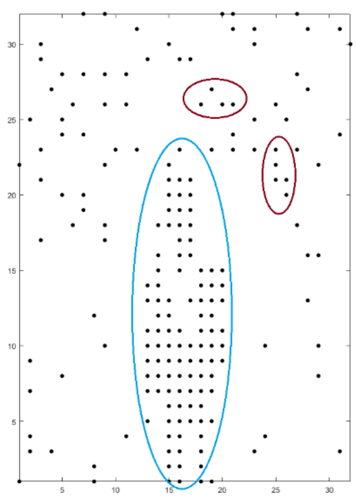

Fig. 6 Connected Domains Extraction

Step III: Feature Point Localization

However, the number of pixels in a connected domain is not such a crucial factor to identify the target as the temperature is. Thus, the sum of temperature $T_i(n)$ in each domain is calculated and the domains with the three highest temperatures are picked as candidate domains which are denoted as $C_i(n)$ circled in Fig. 6. At this moment, rest of the connected domains caused by random noises have been eliminated as interfering information.

In the activity recognition algorithm, the head of the target is selected as the feature domain, because the other part of the target may be blocked by clothes. To identify the feature point from the three candidate domains, all the pixels of $C_i(n)$ are scanned from the top down. The pixel in the middle of three consecutive ones or more in a row is defined as the feature point $P(n)$. The candidate domain which includes $P(n)$ is called the feature domain $F(n)$. In Fig. 7, point A is marked as the feature point.

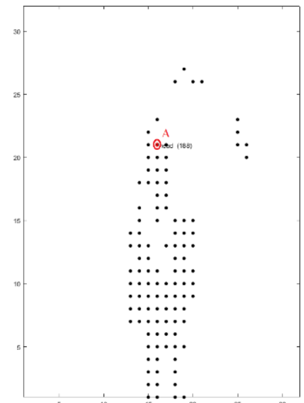

Fig. 7 Feature Point

Step IV: Activity Recognition

The activity of tracking target will be recognized once after it is located in room. If the feature point cannot be found in 10 consecutive frames and the temperature of feature domain $F(n-1)$ is close to the background temperature, the system will show "off-room", which means the target is out of room. Otherwise, the system will continue activity recognition.

There are two states of activities: “quiescence” and “active”. In “active” state, two kinds of activities will be recognized, namely “fall” and “movement”.

If the feature point cannot be found in 10 consecutive frames, but the temperature of feature domain $F(n-1)$ is much higher than background temperature, in another word, it meets the requirement $\sum_{i=n}^{n+9} T_{F(n-1)}(i) \geq 5 * T_{F(n-1)}(n-1)$, the status of target is determined as “quiescence”.

During the period between $(n-6)^{th}$ frame and n^{th} frame sum of longitudinal displacements are larger than 15 pixels, meanwhile sum of lateral displacements are smaller than 10 pixels, the activity will be recognized as "fall".

Otherwise, the activity of the target is identified as “movement”, because there is no significant longitudinal displacement of the feature point. lei

B. Measurement Results and Discussions

Laboratory experiments are carried out to test the proposed algorithm. The experiment results include 30 off-rooms (OFF), 30 quiescence (Q), 50 falls (F), and 50 movements (M). The results are shown in TABLE I

According to TABLE I, the accuracy obtained by the proposed algorithm of detecting off-room, quiescence, fall and movement are 96.7%, 100%, 100%, and 86% respectively, namely the overall accuracy of detection is 95%. What impresses us most is that the accuracy of fall detection is 100%, which means all falls can be detected by using the proposed algorithm. However, some activities such as fast sitting and squatting are mistakenly identified as falls due to their lack of lateral displacement, thus leading to the relatively low accuracy of movement detection.

TABLE I
ACTIVITY RECOGNITION RESULTS

test / real	Off	Q	F	M	Total	Correct	Accuracy
OFF	29	1	0	0	30	29	96.7%
Q	0	30	0	0	30	30	100%
F	0	0	50	0	50	50	100%
M	0	0	7	43	50	43	86%
Total	29	31	57	43	160	152	95%

IV. CONCLUSIONS

In this paper, an indoor human body tracking and activity recognition system with a low resolution thermopile imaging array sensor is proposed. The sensor installed on a wall observes target in the laboratory and detects off-room, quiescent, fall or movement by a new algorithm. Experiments show that the proposed algorithm can be used to determine whether the target is active in the experiment area and identify a fall. The overall accuracy of detection reaches 95%. Therefore, the system we proposed is a promising technology to be used to serve elderly people.

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