Bathroom monitoring with 79 GHz UWB radar sensor using hidden Markov model

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Abstract: In this paper, we present a bathroom monitoring sensor system using a 79GHz ultra-wideband radar sensor. It offers low privacy and anti-humidity capability unlike imaging sensors and IR sensors. It is designed to detect various dangerous states such as falling and drowning with Hidden Markov Model (HMM). We conducted experiments in order to show the effectiveness which is also compared with a conventional scheme. It has been found that our proposed scheme is more accurate than the conventional method.

Keywords: bathroom monitoring, millimeter-wave, UWB, hidden Markov model.

Classification: Sensing

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1 Introduction

Japan is facing a super-aging society, and the number of domestic accidents caused by the elderly is increasing. Especially, the accident frequently arises in bathroom. According to the Ministry of Health, Labour, and Welfare, it is estimated that the number of victims, who drowned after falling unconscious while taking a bath at home, is approximately 19,000 [1]. A typical Japanese bathroom is equipped with a shower and a deep bathtub (Please note that a toilet is usually located in an entirely separate room) and a bather soaks in the hot bath. Most of the accidents are incurred by heat-shock in the bathroom. Taking a bath on a cold day, for example, the elderly suffer from heart stroke or cerebral infarction and experience dizziness, fainting, and sudden blood pressure changes. Also, since their privacy must be specially secured in a bathroom and a toilet room, it is difficult to inform the accidents or to be known. Therefore, a bathroom monitoring sensor system to detect the accident in the early stage is expected [2, 3].

There are several types of wireless sensors such as camera, IR (Infrared), and Doppler sensor. However, these are difficult to be used in a bathroom due to privacy infringement, humidity, and fluctuations in the bathwater. Therefore, several bathrooms monitoring radar sensor systems have been suggested with AI algorithm [4, 5, 6, 9, 10]. In [4], a sensor with a feature extraction algorithm has been reported to cope with the waving of bathwater. In [5], the use of a support vector machine (SVM) has been proposed in order to realize an optimized state estimation for each bather. The learning of SVM requires training data with labels that represent the bather’s state in the learning process. However, the labels cannot be obtained automatically after once setting up the system. In [6], the sensor system with K-means has been proposed as an AI algorithm without the label [7], but it may occur over-fitting due to variation of environment and individual. In this paper, we propose a state estimation scheme using a hidden Markov model (HMM) [8]. The behavior and the state of the bather are modeled by the HMM [9]. The HMM is expected to improve the problem caused by the environment and individual variations. We conduct experiments to show the effectiveness of our proposed method and compare it with a conventional method using K-means [6].

2 Bathroom monitoring system

A 79GHz radar has many advantages as high range resolution, anti-multipath capability, and small size. In this paper, we employ a 79 GHz UWB radar sensor
shown in Fig. 1(a). 77–81 GHz band offers up to 4 GHz of bandwidth, which improves range-resolution. The high range-resolution results in better separation with multipath within a bathroom. The radar adopts a fast chirp modulation scheme which outputs three-dimensional intensity consisting of distance, angle, and relative velocity axes.

When placing the sensor on a bathroom wall, we divide the range area into three subareas according to the distance from the sensor and define them as bathing area, washing area, and wall area, respectively (Fig. 1(b)). The proposed method is composed of three processes.

1. Entrance monitoring
2. Location estimation
3. Accident detection

In entrance monitoring, the system detects the motion of “entry” and “leaving”. If there are bather’s movement at entrance, system output the detection result in location estimation. The bather’s movement is expressed by a standard deviation of the signal on range-spectrum.

In location estimation, when the system detects the bather’s entry, the system starts the bather’s location estimation based on the transition model of HMM. Training data of HMM is composed of two kinds of features as area motion information $P_{r}$ and area Doppler information $P_{d}$. $P_{r}$ represents the bather’s body motion in each range area. It is calculated as follows

$$P_{r}(t) = \sum \sigma_{x}(t, r)$$

Fig. 1. UWB sensor device and experimental environment.
where $\sigma_x$ is a standard deviation each range bins $r$ and it is increased by bather’s body motion. The subscript $x$ represents range-spectrum. The variable $t$ is the frame time of the acquired range-spectrum.

On the other hand, $P_d$ represents the Doppler effect in each area. The Doppler effect occurs from the bather’s movement. It is calculated as follows

$$P_d(t) = \sum x_{mti}(t,r)$$

(2)

where $x_{mti}$ is range-spectrum applied MTI (Moving target indication) processing. MTI processing extracts signal with the Doppler effect.

In the system, the bather’s location is estimated based on HMM. We adopt an ergodic HMM with seven states shown in Fig. 1(d). HMM is estimated by an iterative Expectation-Maximization algorithm as a model with Gaussian mixture emissions. The initial parameters of the Gaussian mixtures model are determined by analyzing the changes in $P_\sigma$ and $P_d$ for each state. These states are classified into each location defined as empty, washing, and bathing, shown in Fig. 1(d).

In accident detection, the system estimates an accident by the body motion of the bather during the bathing process. The body motion is calculated from the $P_\sigma$ in the bathroom. When the body motion remains as small as an empty state for a few seconds, the process estimates that the bather is in the accident.

3 Experiments

We conducted experiments in the bathroom in our university dormitory. Figure 1(b) (c) shows the experimental environment. The 79 GHz sensor (Texas Instruments IWR1443 radar module) is placed next to the bath remote controller on the wall as shown in Fig. 1(c). Table I(a) shows the sensor specification. Three scenarios are assumed as shown in Table I(b). In scenario A, any accidents are not considered. On the other hand, scenarios B and C include accidents due to drowning in the bathtub and falling on the floor, respectively. The subjects performed eight times for scenario A and four times for scenario B and C. Please note that the bathing time for each scenario was unified at one minute in order to compare the change in feature values by behavior. We use the scenario A data six times as training data for the HMM. The experimental results are also compared with the results of the K-means method [6].

| Table I. Specification for experiment |
|--------------------------------------|
| (a) Specification of the sensor      |
| Parameter               | Specifications |
| Center frequency  | 79 GHz          |
| Bandwidth            | 3.3 GHz         |
| Transmission power  | 0 dBm           |
| Sample rate          | 5.0 fps         |
| (b) Scenarios in detail |
| Scenario A             | Scenario B    | Scenario C   |
| Entering to the bathroom | Washing area |             |
| Soaking in the bathtub | Getting out of the bathtub | Drowning in the bathtub |
| Exit from the bathroom |                           |             |
It is noted that the experiment was conducted for our lab students (subjects) under a protocol approved by The University of Kitakyushu and the informed consent was obtained for all subjects.

4 Results

The experiments were conducted for three subjects (males with the ages ranging between 22 and 27), A, B, and C according to the above scenarios. Figure 2 shows examples of the estimation results (left) and evaluation criteria (right). It should be noted that, since the accident detection requires several frame to evaluate the bather’s motion, the accident detection is later than the truth. Two evaluation criteria are set for the detection rate and false alarm rate (FAR). The detection rate represents a precision rate of state detection and accident detection, and they are called state detection rate (SDR) and accident detection rate (ADR). FAR represents the rate of misdetection of the accident.

![Fig. 2. Examples of state estimation results and detection rate in three scenarios.](image)

The average SDR for the K-means method is around 80%, and the SDR decreases according to the increase of FAR. The misdetection of state in scenario A is caused by false alarm of the accidents. The ADR in scenario C is lower than the other scenarios. The feature of falling down is similar to that of leaving the bathroom. The K-means method often causes misdetection of falling down due to fluctuations in the bathwater. In the proposed method, the average SDR is more than 90%. Since the algorithm with HMM suppresses the misdetection, the FAR for scenario C is less than the K-means method.

5 Conclusion

In this paper, we have proposed a bathroom monitoring system using an HMM algorithm incorporated with a 79 GHz UWB radar sensor. We conducted experiments
to show the effectiveness which is also compared with a conventional scheme. It has been found that the accident detection rate is 87–98% which is more accurate than the conventional scheme.