Fall Detection System for Elderly based on 2D LiDAR : A Preliminary Study of Fall Incident and Activities of Daily Living (ADL) Detection

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***Abstract*—FDS (Fall Detection System) is a technology that is very essential for the elderly, in order to immediately get help when the fall incident happens. This paper aims to build a FDS dedicated to the elderly. We propose 2D LiDAR as the main sensor in FDS. In this case, 2D LiDAR has the duty to obtain information data in a room. FDS is demanded to be able to distinguish between fall incidents and ADL (Activities of Daily Living). This paper presents trials on various positions of the human body that can be detected as fall incidents or ADL. The trials aim to produce a dataset that will later be processed using K-NN and RF as a fall detection algorithm. From the results of the trials, 2D LiDAR sensor data can describe two information as detection points. RF produces accuracy up to 94% and K-NN produces maximum accuracy of 100%.**

Keywords—Fall Detection System, Elderly, 2D LiDAR, K-Nearest Neighbor, Random Forest

I. INTRODUCTION

Beside illnesses, falls are a cause of death from injury in the elderly. According to WHO, 33% of elderly people have experienced at least one fall and the rest have fallen more than once during their lifetime. Some areas that falls commonly occur are hallways, bathrooms, kitchens and bedrooms [1]. Elderly people have a risk of falling due to many factors including decreased physical and psychological conditions, loss of consciousness, vision problems, joint problems, respiratory problems, heart failure, and other health problems. The older we get, the more the risk of death from fall incidents [2]. The elderly generally live alone whether temporarily or daily. Thus, it is necessary to establish a real-time fall incident detection system. The results of this detection system will later be sent to family members via smartphone. This paper focuses on the process of detecting fall incidents activities.

Researches on FDS (Fall Detection System) have been done in various ways: visionary / camera-based FDS, wearable-based FDS and ambient-based FDS [1]. In FDS technology, Kinect camera sensors have been used to distinguish between fall incident and other activities that are not included in fall incident [3]. The use of a camera allows fall incidents to be detected based on analysis of body movements and body position [4]. The use of Pi Camera in FDS has advantages, namely it has a good performance and it is also low cost [5]. In further development, RGB-D (Red, Green, Blue - Depth) image processing has been developed to address privacy issues [6], [7]. Even though, generally the elderly will feel uncomfortable with the camera recording process, especially in a private room such as bathroom [8]. The main problem in camera-based FDS is that there is no research that proves that camera can work in a very dark and no light environment.

In a wearable-based FDS, detection of fall incidents is done by installing a number of sensors located around the body. The 3D accelerometer sensor placed on stomach was once used as a fall detection [9], [10]. An accelerometer is also placed on the user's hand or thigh to detect fall incidents [11], [12]. The main problem of wearable sensors is that it can be a trouble for users. Elderly people tend to become forgetful in doing things. Therefore, there is high possibility that the sensor is not installed.

In an ambient-based FDS, various sensors are deployed ranging from ultrasonic, motion sensors, sound sensors, radars and others to detect fall incidents in a room [13], [14]. FDS has been proposed by using the radio frequency wave propagation model [15]. However, this method requires complicated preparation. FDS was once proposed by installing sensor arrays on a carpet to monitor the activities of elderly [16]. The problem with ambient sensor-based FDS in general is a complicated setup process [1].

To overcome this problem, we propose 2D LiDAR (Two Dimension Light Detection and Ranging) to be used as FDS. The reason for proposing LiDAR in FDS is, when compared to camera based FDS, LiDAR is not affected by changes or lack of light intensity. Compared to wearable based FDS, the application of LiDAR does not limit the comfort of the elderly in doing their daily activities. The set up on LiDAR is very simple and just to be placed in one corner of the room to scan objects. Thus, there is no need for a combination of sensor types, and there are no sensor placement problems as in the existing ambient based technology. Although LiDAR is more popular to be applied in terms of navigation such as UAV [17], autonomous mobile robot [18], autonomous vehicle [19], we assume that 2D LiDAR can be used to detect fall incidents. Fall incidents detection can be done by analyzing the difference in data taken when the room is empty and when there are people doing activities in the room.

As general, this paper is still in preliminary stages. This paper does not discuss the comparison with previous research [1], [3 – 16]. This paper only proposes and tries to develop other ways to build ambient-based FDS. We consider the classical K-NN and RF algorithms to be very suitable for preliminary stage of our work. Furthermore, this paper is organized as follows. Section II describes previous researches related to machine learning methods used in FDS, specifically in detection. We discuss the concept LiDAR-based FDS in section III. This section also discusses sensors, environments for trials, datasets and features. In section IV, we tested the two methods we used, compared them and analyzed the results. Finally, Section V contains conclusion from all of the works that we do.

II. Related Work

Our work requires learning algorithms to perform detection tasks. K-NN is one of ten detection algorithms that are very simple and easy to used [20]. In this study, we need a comparison algorithm which also has good detection performance. One of them is a decision tree algorithm that is not too complex [21]. In this case, we chose Random Forest (RF) as a comparison algorithm which derived from the development of a decision tree algorithm. For this reason, we use these two algorithms. K-Nearest Neighbor (K-NN) and Random Forest (RF) were proposed for ambient-based FDS [1] and wearable-based FDS [11]. In that research, RF and K-NN are successfully implemented and have high accuracy in the dataset produced by the gyroscope and accelerometer. RF and K-NN are also well implemented in FDS-based cameras using analysis of key points variation of human skeleton [22]. In another studies, RF and K-NN have also been implemented in FDS especially fall from bed [23]. With various considerations from the previous papers, then in this paper, RF and K-NN are used as an algorithm for detection of fall incidents in LiDAR-based FDS.

III. 2D LiDAR-based FDS

A. *Our Work*

Our work in this paper is to build an ambient-based FDS using 2D LiDAR to detect fall incidents in the elderly. The FDS that is built must be able to detect fall incidents by recognizing differences in sensor data, both during daily activities (ADL) and when the incident occurs. To perform the proposed FDS, the system design is arranged as shown in Figure 1.

1) 2D LiDAR functions as the main sensor that has the task to collect information in a room.
2) The results of the trials in the ADL and fall activities produce two trial data then it combined into a single dataset.
3) A single dataset will later be split into data training and data testing. The percentage split between training and testing will be searched until obtain optimal accuracy
4) The dataset is processed using K-NN and RF for detection of fall incidents. The output of the two algorithms is ready to use fall incident information.
5) The detection accuracy of the two algorithms are compared.

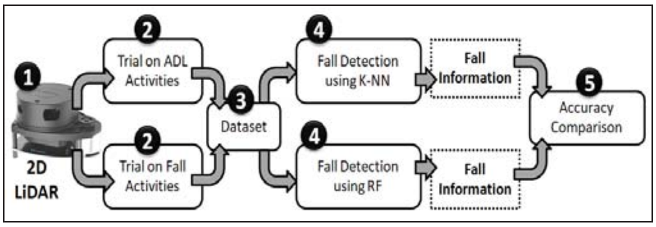


Fig. 1. System Design

B. *Sensor and Environment*

In the proposed FDS, we use the RP LiDAR A1 as the main sensor. This sensor works with the ability to scan two dimensional objects on 360 degrees. In scanning, the sensor emits infrared laser light with a wavelength of 785 nm with a maximum scanning distance of 12 meters.

In this study, the sensor is not installed in the center of the room. Instead, it is installed on the side of one wall of the room. Thus, the sensor scanning angle is assumed not 360 degrees but rather 180 degrees. Even though the sensor's ability can detect 360 degrees. In addition, the sensor is placed 10 cm above the floor (calculated from the surface of the floor to the sensor’s eye). Fig. 2 shows sensor configuration. Fig. 3 shows the room plan used for the trial.

Fig. 2. Sensor Placement

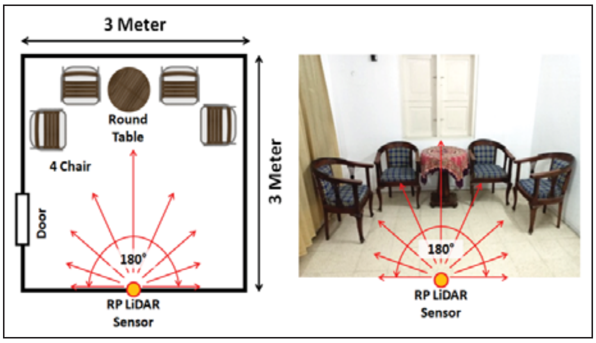


Fig. 3. Room Spesification

C. *Dataset and Feature*

When the LiDAR sensor does the scanning, the information is obtained in every 1° distance of the maximum scanning of 360°. If it is assumed that the sensor is placed on one wall of the room, then the sensor only produces information at every 1° of 180° distances. Thus, the features processed in the detection algorithm are 180 features.

Then, ten male volunteers with weight, height, average age (75 kg, 170 cm, 30 years old). In this case, we do not involve the elderly when conducting trials. Each volunteer demonstrates six activities consisting of three ADL (An Empty Room, Standing Up / Walking, Sitting Down) and three falling activities (Falling Transversal, Falling Longitudinal, Falling Oblique). These six activities are demonstrated when the room is sufficiently lit. From the results of the trials, 60 lines of dataset are obtained. Then the trials are conducted again in the dark room. From the results of the trials, we get 60 more lines of dataset. Thus, the lines of dataset become 120. Because the feature used in this study is 180° distance information, the dataset in this study is a matrix with a size of 120x180. Because the features obtained are the results of scanning sensors, the dataset in this study is referred to as primary dataset. In this study, the dataset are used for detection tasks. The purpose of the detection is to clearly describe the presence or absence of a fall incident. There are only two information, ADL or Fall.

IV. Result and Discussion

A. *Sensor Trials on ADL*

These trials were conducted to find out various activities except falling that can be recognized by the sensors. Various activities performed by a volunteer. There are three activities that have a significant difference in sensor data namely, an empty room, standing up or walking, and sitting down as shown in Table I. The trial is conducted in a dark room even darker than the picture in Table I to prove that the LiDAR sensor can work well in a dark room. This is shown from the sensor data when detecting objects and home furniture in a dark room. Sensors can detect objects such as when the object is standing up, sitting, or not in the room.

B. *Sensor Trials on Fall Activities*

Same as previous trial, these trials were conducted to find out various falling activities that can be recognized by the sensors. There are three activities that have a significant difference in sensor data namely, falling transversal, longitudinal and oblique towards the sensor as shown in Table II. This trial is also conducted in a dark room, the same as in the previous trial.

TABLE I. Sensor Trials on ADL

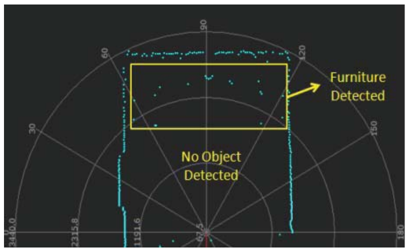
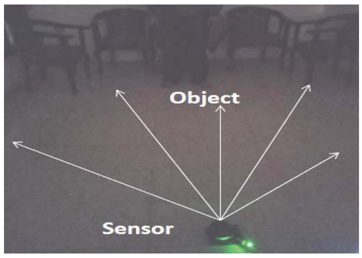
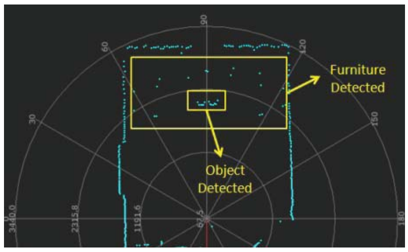
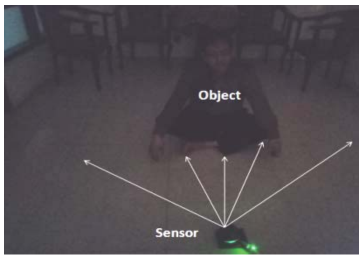
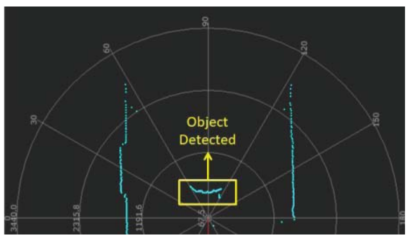
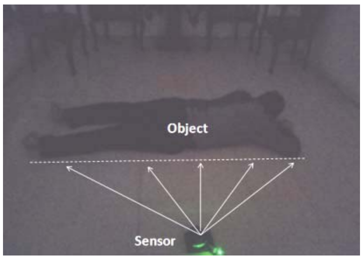
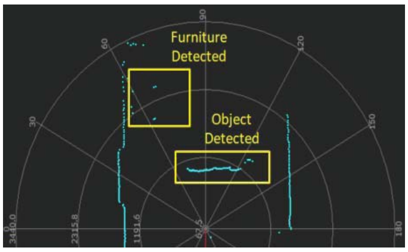
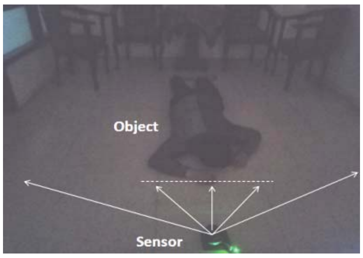
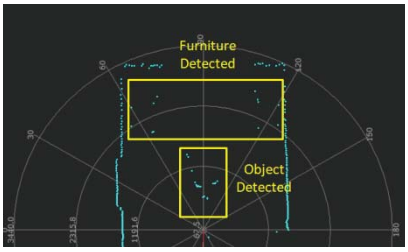
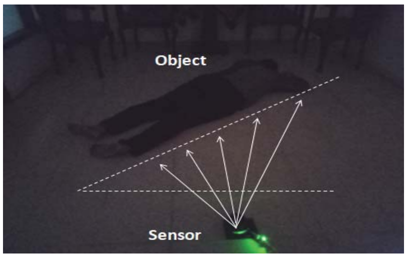
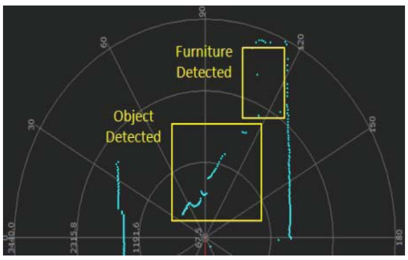
An Empty Room	**Activities**	
	Data Sensor	
Standing Up / Walking	**Activities**	
	Data Sensor	
Sitting Down	**Activities**	
	Data Sensor	

TABLE II. SENSOR TRIALS ON FALL ACTIVITIES

Falling Transversal Towards the Sensor	**Activities**	
	Data Sensor	
Falling Longitudinal Towards the Sensor	**Activities**	
	Data Sensor	
Falling Oblique Towards the Sensor	**Activities**	
	Data Sensor	

C. K-NN Accuracy

The K parameter in the K-NN algorithm is the parameter that its optimal value must be found. In addition, the percentage of data training and testing is also a parameter that its optimal value must be found. The optimal value of the two parameters will produce maximum accuracy. For this reason, the purpose of this trial is to find the optimal K value and percentage split (training%, testing%). By using the standard K-NN library on the python platform, the results are as shown in Fig. 4. The trial results show that the maximum accuracy of K-NN in this trials is 1.0 from the range (0.0 to 1.0) or 100% in range percent. Maximum accuracy is achieved when K = 2 and percentage split (90%, 10%).

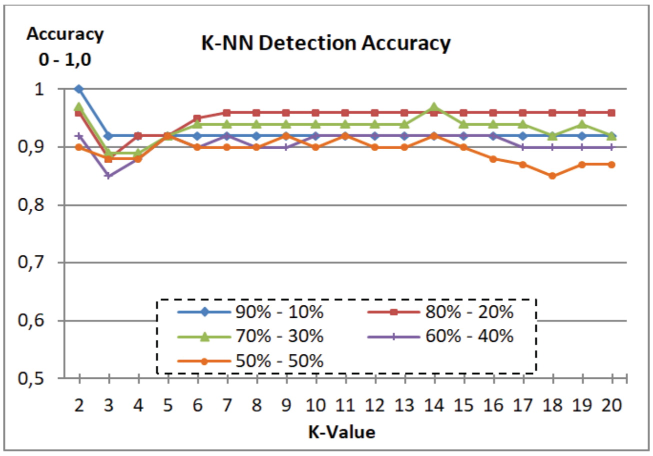


Fig. 4. K-NN Accuracy in Detection Mode

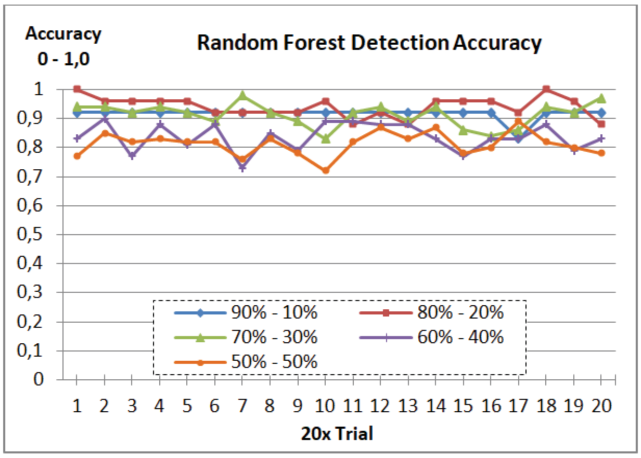


Fig. 5. RF Accuracy in Detection Mode

D. RF Accuracy in Detection Mode

The purpose of this trial is to get an optimal accuracy by finding the optimal value of the percentage of data training and testing. In contrast to KNN, the RF algorithm does not recognize the parameter K. Thus, the parameters sought for their optimal value are only percentage split (training%, testing%). However, in these trials, accuracy values vary at various percentage split values (training%, testing%). For this reason, the accuracy value is taken from the average accuracy of 20x trials. Fig. 6 shows the results of 20x trials on various percentage split values (training%, testing%). The trial results show that the maximum RF accuracy in this trial is 0.94 from the range (0.0 to 1.0) or 94% in range percent. This maximum accuracy is the average value of 20x trials when percentage split (80%, 20%).

E. Discussion and Methods Comparison

From the results of trials III A and III B, using a single 2D LiDAR sensor, there are six activities that have a significant difference in data, namely, an empty room, standing up/walking, sitting down, falling transversal, falling longitudinal and falling oblique toward the sensor. Then, from six activities categorized into two information, Fall and ADL. The proposed FDS must also be able to detect two information namely Fall and ADL. RF algorithm produces an detection accuracy up to 94%. Meanwhile, the K-NN algorithm shows better results up to 100%. Thus, the number of datasets used in this study are enough to perform the detection task. However, this paper is still in the preliminary stages of work. Need to improvement of feature number and size of the dataset.

V. Conclusion

This paper proposes to build an FDS dedicated to the elderly by using the 2D LiDAR sensor. This proposal is alternative option in building an FDS, with the advantage of having a LiDAR sensor implementation that is not affected by light intensity, so that it can still detect well in dark room. Overall both methods show good performance. K-NN shows better performance than RF This is indicated by the maximum accuracy value that reach.

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