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***Research Article***

# Pedestrian and Mobile Robot Detection with 2D LIDAR

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**Abstract**

The first problem to be overcome in robotics is the positioning of the robot and surrounding objects. Detection and positioning of moving objects around the robot are an important point to prevent accidents. Deep learning and 3D LIDAR technology are often used, especially in pedestrian detection. Although these studies have high performance, they are not widely used yet due to their high cost. In this paper, a robot and human sensing system is proposed for use in lower cost 2D LIDARs. The system detects robot and human beam patterns by scanning the 2D LIDAR beam with the sliding window. Thanks to the sliding window technique, it marks whether there is a robot or a human in the part it scans. A new end-to-end deep neural network architecture is proposed in this study for pedestrian and mobile robot recognition based on 2D LIDAR data collected in a simulation environment. It has been observed that the system perceives robot and human models in a static environment with 91.6% accuracy.

**Keywords:** LIDAR, Pedestrian Detection, Mobile Robot Detection, Positioning, Machine Learning

# 2B LIDAR ile Yaya ve Mobil Robot Algılama

**Öz**

Robotikte aşılması gereken ilk sorun, robotun ve etrafındaki nesnelerin konumlandırılmasıdır. Robotun etrafındaki hareketli nesnelerin algılanması ve konumlandırılması, kazaları önlemek için önemli bir noktadır. Derin öğrenme ve 3B LIDAR teknolojisi, özellikle yaya tespitinde sıklıkla kullanılır. Bu çalışmalar yüksek performansa sahip olmalarına rağmen yüksek maliyetleri nedeniyle henüz yaygın olarak kullanılmamaktadır. Bu makalede, daha düşük maliyetli 2B LIDAR'larda kullanılmak üzere bir robot ve insan algılama sistemi önerilmiştir. Sistem, kayan pencere (sliding window) ile 2B LIDAR ışını tarayarak robot ve insan ışın modellerini algılar. Kayan pencere tekniği sayesinde taradığı kısımda robot mu insan mı olduğunu işaretler. Bu çalışmada, bir simülasyon ortamında toplanan 2B LIDAR verilerine dayanan yaya ve mobil robot tanıma için yeni bir uçtan uca derin sinir ağı mimarisi önerilmiştir. Sistemin robot ve insan modellerini statik ortamda %91.6 doğrulukla algıladığı görülmüştür.

**Anahtar Kelimeler:** LIDAR, Yaya Algılama, Mobil Robot Algılama, Konumlandırma, Makine Öğrenmesi

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# 1. Introduction

The first problem to overcome in robotic applications is the detection and navigation of the robot and surrounding objects (Borenstein et al., 1997; Siciliano & Khatib, 2016; Seçkin, 2020). The ideal working environment for robotic applications is that objects other than the robot itself are static. However, this is not possible in real life. In places where robots are frequently used, the dynamic obstacles that robots encounter most often are people. Especially nowadays, many studies on smart vehicle technology and navigation of autonomous guided vehicles (AGVs) deal with the perception of humans and other dynamic objects. To detect pedestrians, the robot must first be able to detect the environment and other dynamic objects. Then, it is necessary to accurately distinguish the position of pedestrians and other dynamic objects and plan the vehicle's path plan accordingly. The detection of pedestrians and other dynamic objects is an essential point for avoiding material and moral accidents that may be caused by the robot.

In pedestrian detection studies, LIDAR and various cameras are usually used. However, in recent years, the systems of LIDAR have been more preferred because the camera systems are greatly affected by the light intensity. Researchers have shown very successful applications in studies on this topic especially with Deep Learning (Chen et al., 2017; Lang et al., 2019; Qi et al., 2018). However, high resolution data is used for high performance which involves high processing load and expensive hardware. The type of lidar used in high performance applications are sensors often referred to as 3D or multichannel LIDAR (Börcs et al., 2017; Kidono et al., 2011; Spinello et al., 2010; Wang et al., 2017). However, since these types of LIDARs are quite expensive today, they are mostly preferred for autonomous vehicle technology.

2D LIDAR provides a one-layer point cloud and is much cheaper than 3D, which is why it is preferred in systems such as AGVs. Pedestrian detection using 2D LIDAR is mainly done by detecting the projection of pedestrians' legs and/or feet onto the sensor (Li et al., 2017). The projection onto the sensor does not produce a standard pattern due to the pedestrian's posture (standing, walking, or running) and this data also contains noise due to robot motion and sensor measurement error. For this reason, the pedestrian pattern on the LIDAR can be easily confused with other moving objects. There are few studies on pedestrian detection using 2D LIDAR and these studies generally deal with pedestrian detection in indoor spaces such as offices (Arras et al., 2007; Shao et al., 2007). In some studies, sensor fusion with camera systems has been performed to achieve higher performance (Cristiano Premebida et al., 2007; Oliveira et al., 2010; Lin & Lin, 2016).

This study aims to contribute both pedestrian and robot detection in a indoor area simulation environment as a contribution to the literature. Such studies exist in the literature only as pedestrian and vehicle detection (Machida & Naito, 2011; Cristiano Premebida et al., 2007; Yang et al., 2018). But these systems are not designed over 2D LIDAR systems. There is a lack of detection of pedestrians and moving objects in indoor environments such as factories, houses, or workplaces. In the study, a low-cost system operating in an indoor area was simulated. In this paper, a system is developed that can detect and position pedestrians as well as other robots using 2D LIDAR technology. It is aimed that the designed system can detect multiple humans and robots moving at different speeds. For this purpose, a new end-to-end deep neural network architecture for pedestrian and mobile robot recognition has been proposed in this work based on 2D LIDAR data collected in the simulation environment. In the next part of the study, the material used, and the proposed method are presented. Then, the findings obtained with the system are presented and discussed.

# 2. Material and Method

The method developed for this purpose is to collect and label dataset in a known environment and use Deep Learning to recognize pedestrians and robots. CoppeliaSim was used as the simulation environment (Rohmer et al., 2013). The operations in the simulation environment are performed using Python programming language and CoppeliaSim remoteApi was used for this purpose. In the next part of this section, the process of data collection process from the simulation environment and the designed deep learning model is presented, respectively.

## 2.1. Data Collection for Pedestrian and Mobile Robot Signal Pattern Recognition

For data collection, an indoor area with 3 rooms is designed as shown in Figure-1. In the area, there are 5 human models and 5 mobile robot models. The human and robot models are set to run at random speeds and directions in each simulation. In this way, it is aimed to obtain different patterns. Also, in the system, it is possible for multiple dynamic objects to enter the LIDAR scanning area at the same time. 3 fixed LIDARs were placed in the area. The type of LIDAR sensors is Hokuyo URG-04LX. The scan angle of this sensor is 240 degrees, the measurement distance is 4m, and the scan time is 100ms (*Scanning Rangefinder Distance Data Output/URG-04LX Product Details | HOKUYO AUTOMATIC CO., LTD.*, n.d.).

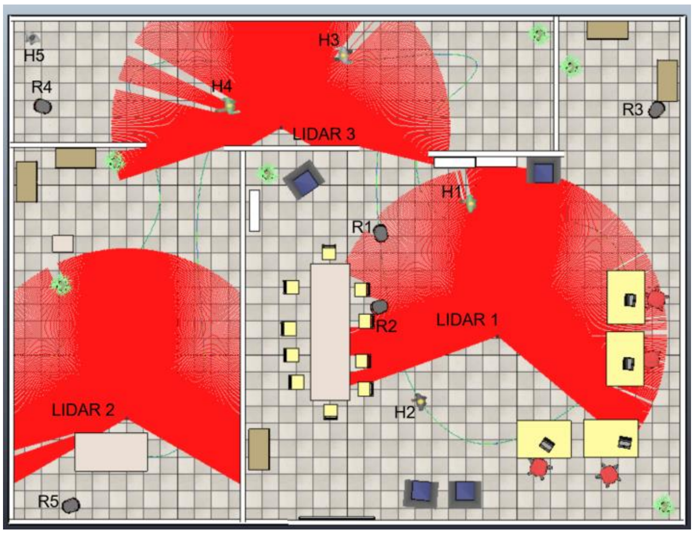


*Figure 1. Simulation Environment*

The exact positions of pedestrians and robots can be obtained from the simulation environment. In the data recording, during the simulation, it is recorded whether pedestrians and robots are in the senor scans and where they are. The exact positions of people and robots within the coverage area of the sensors are taken and their positions are labeled during scanning as in the examples shown in Figure-2. The total number of sample data collected in the simulation is 1732. The number of points that 2D LIDAR measures in one scan is 684 in one sample. There are three columns in the dataset for each of its dynamic models (robot and human models). The first column is whether the dynamic model is in the coverage area. If the model is in the coverage area of lidar, it is marked with a 0 if not 1. The other two pillars are the distance and angle of the model to LIDAR. If the model is not within range, these two column values are entered as -1. Robot detection and human detection columns used as outputs in the data set are marked as 1 if there is a dynamic model, 0 if there is no.

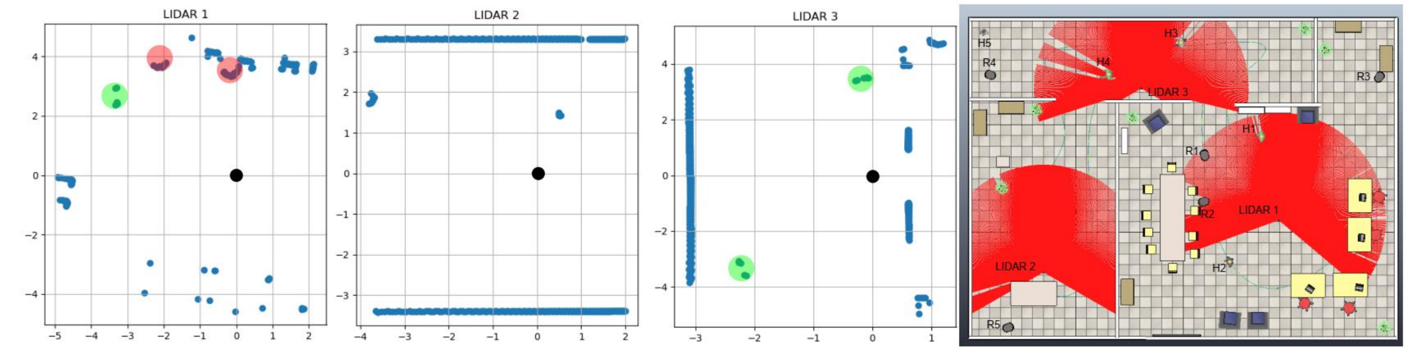


*Figure 2. Dataset Collection and Labeling Pedestrian and Robot*

## 2.2. Deep Neural Network Model for Pedestrian and Mobile Robot Detection

Deep Neural Networks (DNN) is a system that allows computational models consisting of multiple processing layers to learn representations of data with multiple abstraction levels (LeCun et al., 2015). It has gained a lot of attention in the artificial learning field over few years, and it has radically affected the Computer Vision (CV) area. Deep learning is actually a subfield of machine learning, but the applications and designed networks in this part have attracted such attention that it can be perceived as a new field. The methods used in deep learning are more advanced than traditional machine learning methods and provide a great advantage in terms of overcoming the difficulties of extracting features from data by themselves. The process of selecting best features is tremendously time-consuming and is often ineffective. Also extending the features to other type of data becomes a problem. There are lots of DNN types because of there are many network architectures and layer types. The main types of layers are convolution, pooling, and fully connected. However, there are also frequently used layer types such as dropout, flatten and activation. Fully connected and dropout layer types were used for the designed network in this study.

Fully connected layer, also known as Dense layer, is generally used in DNN outputs. This layer basically takes all inputs from the previous layer as input to all nodes in it and presents an n-dimensional vector as the output after it. Each node used in this layer is an artificial neural network. Each Dense layer has many parameters such as node number, activation function, bias value. In this study, the dense function of the Keras library was used as a fully connected layer (Chollet, 2015). Only the number of nodes and activation function types were used as variables in the study. The dropout layer is used to prevent overfitting of the extracted model during a learning process(Srivastava et al., 2014). Dropout ensures that a certain number or percentage of nodes are randomly disabled during training and the data used during this time is not included in the training of that node. The function of this layer can be summarized as preventing the nodes in the learning process from memorizing all the data by randomly ignoring some training data.

The DNN used in this study is depicted in Figure-3. The system is designed for classification. Lidar measurement values are taken as input and then these values are passed through Dense and Dropout layers three times. Dense layers were selected with 0.25 intervals between 0.1 and 2 in proportion to the number of input features, respectively. In addition, "relu" and "sigmoid" were used as activation functions. For the dropout layer, values of 0.2, 0.4 and 0.6 were used. For classification of the Dense layer used at the output, the activation function is selected as softmax. If n nodes were used in the Dense (dense_1) layer used in the introduction in the design, half of it was dense_3 for dense_2 and dense_4 in the branches, and n / 4 for dense_5. Since integers are used in layers, rounding is performed in the division operation. The number n was chosen in proportion to the number of LIDAR readings and was chosen as 15, 30, 60 and 90. In this study, the sliding window technique was used on a LIDAR scan consisting of 684 measurements to determine whether there was a human or a robot in the area detected by the robot. Sliding window width is determined as 30. Collected data were not considered as time series. While 70% of the data set was used for training, 30% was used for testing.

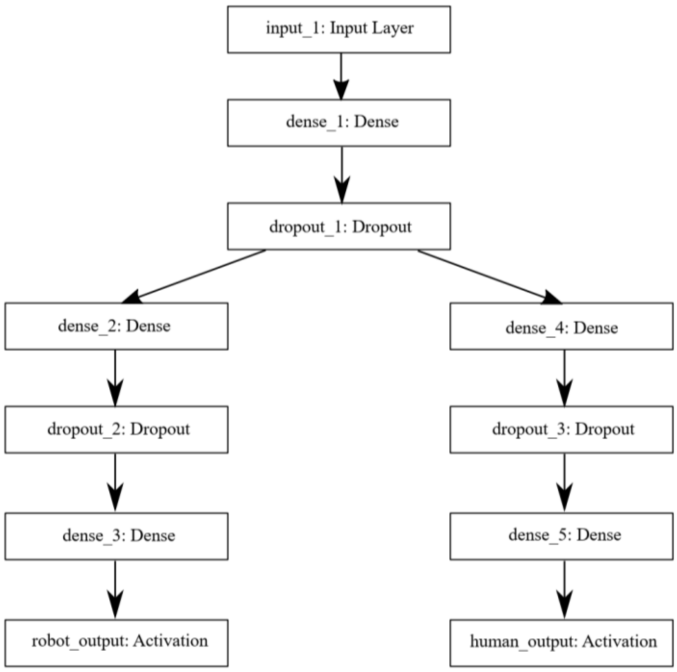


*Figure 3. DNN Structure*

## 3. Results and Discussion

In this study, 1732 data were collected with static 2D LIDARs. The dataset has been trained using different configurations in the deep learning model suggested in the method section. In the train operation, the number of epoch was set to 100 for each configuration and a man-optimizer was used. The configuration models obtained because of the learning were evaluated by 5-fold cross validation. The average time and accuracy values obtained for 5-fold are presented in Table-1. Accordingly, the highest train accuracy value for human detection is 91.18 and it is DNN configuration number 8. For robot detection, the highest accuracy is 91.18 and it is DNN configuration number 14. However, all configurations appear to be very close on average in terms of accuracy values. It is seen that the lowest accuracy values are obtained when the highest percentages of dropout are used. It has been observed that as the number of layers increases, the training time increases. The values produced by these values for 5-Fold are presented in Figure-4 for robot detection and Figure-5 for human detection. As can be seen in these graphs, it is clearly seen that the standard deviation decreases as the number of knots in the layer increases. It has been noticed that the collected dataset is labeled in dynamic objects remaining in areas where the LIDAR beam cannot reach (shaded). Despite this, the overall accuracy has been found to be quite high. When the model taught is applied on a mobile robot, it has been observed that it can even detect multiple dynamic objects, as seen in Figure-6. The method presented in this paper and the methods and results obtained in various studies are compared in Table-2. In the table, the accuracy value is compared as the working environment, sensors used, pedestrian detection, moving object detection, algorithm used and performance metric.

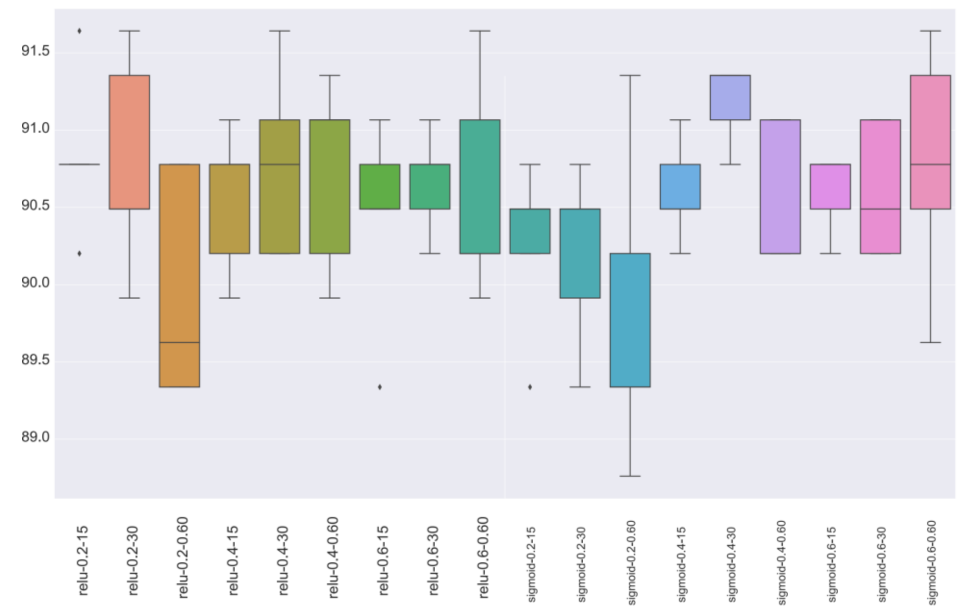


*Figure 4. Robot Detection Accuracy Results*

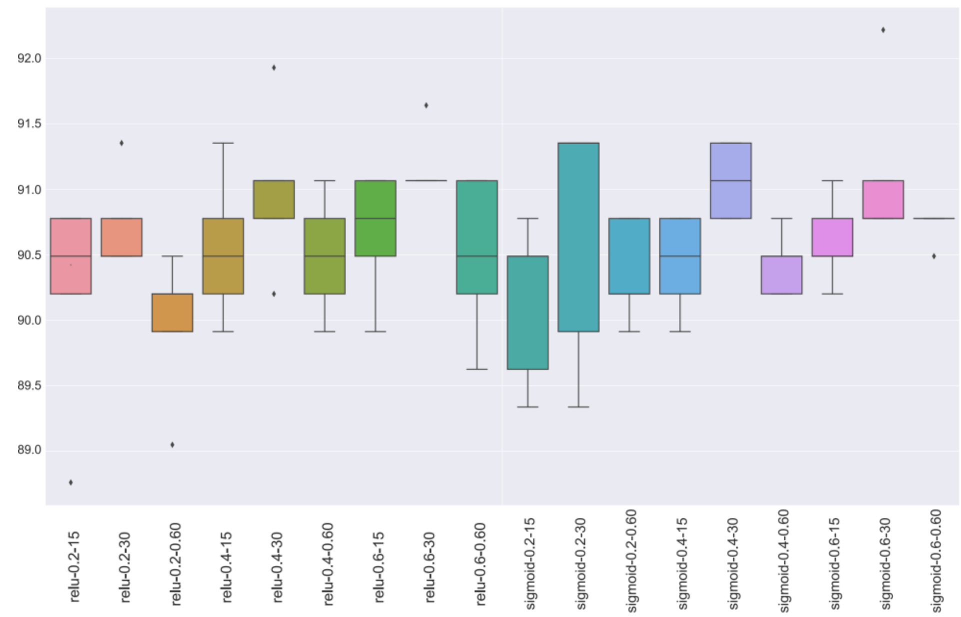


*Figure 5. Human Detection Accuracy Results*

Table 1. Accuracy Results

| DNN Configuration | | | | Training Time (s) | Human Detection Accuracy (%) | Robot Detection Accuracy (%) |
|---|---|---|---|---|---|---|
| No | Activation function | Dense Layers | Dropout percentage | | | |
| 1 | relu | 15-8-4 | 20 | 44.78 | 90.20 | 90.84 |
| 2 | relu | 15-8-4 | 40 | 74.79 | 90.72 | 90.78 |
| 3 | relu | 15-8-4 | 60 | 148.61 | 89.97 | 89.97 |
| 4 | relu | 30-15-8 | 20 | 44.64 | 90.55 | 90.55 |
| 5 | relu | 30-15-8 | 40 | 72.74 | 91.01 | 90.78 |
| 6 | relu | 30-15-8 | 60 | 149.60 | 90.49 | 90.72 |
| 7 | relu | 60-30-15 | 20 | 44.24 | 90.66 | 90.43 |
| 8 | relu | 60-30-15 | 40 | 71.76 | 91.18 | 90.66 |
| 9 | relu | 60-30-15 | 60 | 147.91 | 90.49 | 90.61 |
| 10 | sigmoid | 15-8-4 | 20 | 43.51 | 90.14 | 90.26 |
| 11 | sigmoid | 15-8-4 | 40 | 71.51 | 90.66 | 90.20 |
| 10 | sigmoid | 15-8-4 | 60 | 148.94 | 90.37 | 89.80 |
| 13 | sigmoid | 30-15-8 | 20 | 44.34 | 90.43 | 90.61 |
| 14 | sigmoid | 30-15-8 | 40 | 71.95 | 91.07 | 91.18 |
| 15 | sigmoid | 30-15-8 | 60 | 150.43 | 90.43 | 90.55 |
| 16 | sigmoid | 60-30-15 | 20 | 44.96 | 90.61 | 90.61 |
| 17 | sigmoid | 60-30-15 | 40 | 73.19 | 91.12 | 90.61 |
| 18 | sigmoid | 60-30-15 | 60 | 155.31 | 90.72 | 90.78 |

Table 2. Comparison Table

| Reference | Environment | Sensor | Pedestrian Detection | Moving Object Detection | Algorithm | Accuracy (%) |
|---|---|---|---|---|---|---|
| (Wu et al., 2017) | Real World | 3D LIDAR and Camera (Velodyne VLP-16 and Logitech C920 camera) | Yes | No | PVANET | 99.1 |
| (Cristiano Premebida et al., 2007) | Real World (Dataset) | Camera | Yes | Yes | CNN | 81.61 |
| (C. Premebida et al., 2009) | Real World | 2D LIDAR | Yes | No | FLDA | 80 |
| Purposed Method | Simulation | 2D LIDAR | Yes | Yes | CNN | 91.6 |

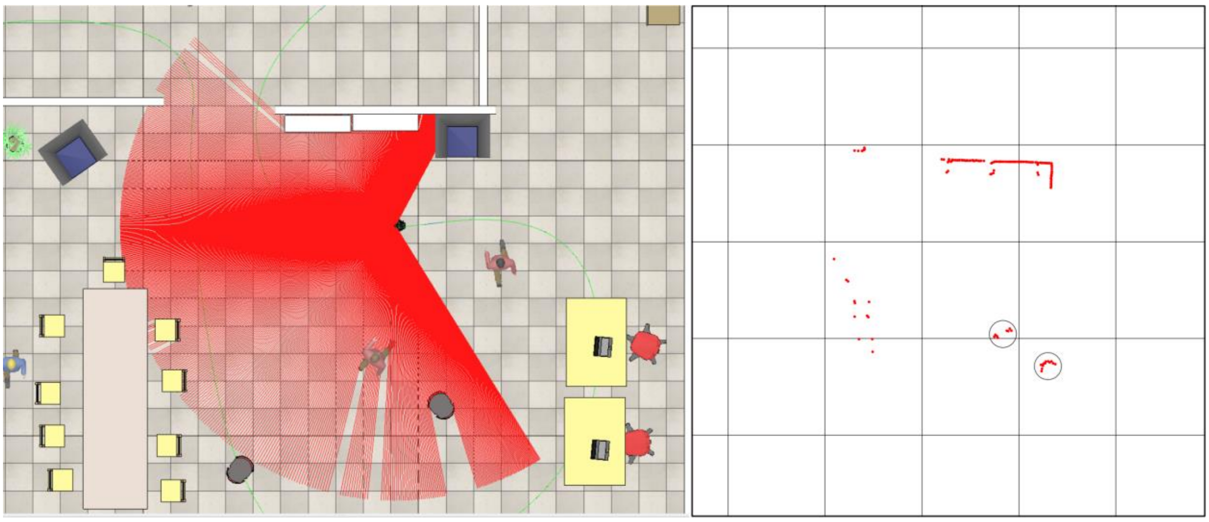

Figure 6. Mobile Robot Dynamic Object Detection

# 4. Conclusion

In this paper, a method that can detect and position pedestrians and other robots using 2D LIDAR technology is proposed. In the designed method, firstly, supervised learning was carried out by collecting the data of static LIDARs and robot and human models whose positions are known. A unique DNN was designed in the study. It has been observed that the system detects robot and human beams in static environment with 91.6% accuracy. Different configurations were tested on the designed DNN and the model with the highest performance was selected and deployed on the mobile robot. It has been observed that the proposed method can detect and position multiple human and robot models moving at different speeds in the simulation environment. The method proposed in the study can be used in the future in the design of service robots such as autonomous guided vehicles, cleaning robots, and in closed area pedestrian and mobile robot detection. With the method, a data set can be prepared beforehand by placing objects that may be in the work area. In addition, the proposed method can also be the basis for accident prevention and occupational safety applications.

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