Real Time Object Edge Detection System to Assist RPLidar Sensor Performance

Arjon Turnip, Nendi Suhendi Syafei, Rehyan Devara, Peri Turnip and Gilbert Sihombing

Abstract— **The covid-19 virus really brings problems to human life, one of which is in the health sector. To overcome this problem, innovations in technology are needed. Today's robotics industry has been able to improve the quality and quantity of human life today. One proof is the presence of a robot that can navigate by itself, this is called an autonomous robot. However, in the navigation path of the robot itself, sometimes it will be faced with objects that are in its path. The object is not predictable by the 2D LiDAR sensor, so when it hits an object, the sensor gets messed up. In this study, a visual object detection method was developed to assist the performance of the RPLiDAR sensor so that the scanning carried out by the RPLiDAR sensor remains stable. This visual object detection method uses the OpenCV library which has functions to process images. The image obtained is a frame of the surrounding environment in real-time. The software used to use this method is the PyCharm IDE. By implementing this method in covid robot research, the covid robot could detect obstacles or detect objects. So that this covid robot could know that there was an object in its navigation path so that the performance of the RPlidar sensor could be maximized.**

Index Terms— **Classification, visual attention, particle swarm optimization, PSO.**

I. Introduction

CURRENTLY, human life is experiencing problems due to the Covid-19 outbreak. In December 2019, the first case of the Covid-19 virus was reported in Wuhan, the capital of China's province of Hubei Sheng [1-2]. After that, the virus quickly spread in Asia, Europe, America, and the rest of the world [3]. The impact of the virus can affect the upper or lower respiratory tract with the main symptoms including fever, cough, shortness of breath, difficulty breathing, fatigue, chills, body aches, headache, sore throat, congestion, runny nose, loss of smell or taste, nausea, and diarrhea [4]. From the impacts that have been mentioned above, this is certainly very influential in the health sector. This impact causes health workers to keep their distance and use PPE or Personal Protective Equipment on a regular basis. This can result in the stock of PPE itself running out.

The development of technology at this time which is increasingly rapidly encouraging people to always create new and more modern innovations in the field of technology. One of the technology industries that is currently growing rapidly is the robotics industry. Robotics technology has now been able to improve the quality and quantity of human life. One of the advancements of the robot industry itself is where when the robot is able to determine its own path to move. So it can be said that the robot has a navigation system. Navigation can be defined as a process to determine a suitable and safe path between the starting point and the destination point where the robot moves. Furthermore, navigation on a robot can also be interpreted as the ability to move in a certain environment, or the science of guiding a robot that can move in that environment. So, when we direct the robot to where, the robot will follow the mapping that has been made.

However, the mapping carried out by the LiDAR sensor can be instantly confused when scanning within the area it is traveling in. One of the problems faced by autonomous robots with LiDAR sensors installed is when the robot will pass through obstacles invisible, such as items in the navigation path that will be passed by the covid robot [5]. This of course will hinder the scanning of the LiDAR sensor, because the scanning will rotate inconsistently. To be able to overcome these problems, these obstacles must be detected visually. To detect obstacles these, a visual-based object detection method is used. This concern arises because the covid robot will of course be implemented in an environment that is not necessarily a good navigation path, due to the possibility of obstacles in visible that will appear unpredictable. Therefore, the design of the COVID-19 robot system must be equipped with object detection capabilities in order to prevent inappropriate scanning by the LiDAR sensor for mapping the navigation path of the autonomous robot.

The use of this visual-based object detection method has actually been carried out in many existing studies, so we can predict that the application of this method will be very useful for tools that use LiDAR sensors. Several studies regarding visual-based object detection methods are: In [6-7] using CNN or Convolutional Neural Networks for classification of facial expressions. The result is a detection rate of 97.6% on 5600 images from > 10 subjects. In [8] also discusses facial expression recognition with the CNN method. Then in [9] also discussed the CNN architecture called MobileNetV2 which is a development of the previous version of Mobile Net. The test is carried out using the COCO object detection dataset and the results show that Mobile Net uses the fewest parameters while still producing good accuracy values. This result is better when compared to the previous version of Mobile Net. This shows that MobileNetV2 can detect objects with low parameter values with a performance that is not much different from other

Arjon Turnip, Nendi Suhendi Syafei, and Reyhan Devara. Department of Electrical Engineering, Universitas Padjadjaran, Indonesia. (e-mail: turnip@unpad.ac.id*).

Gilbert Sihombing. Department of Engineering Physics, Institut Teknologi Bandung, Indonesia.

Peri Turnip. Department of Mathematics, International Women University, Indonesia. (e-mail: peri.turnip@gmail.com

architectures, making it suitable for use on the Raspberry Pi. In [10] also researched using Mobile Net. The Mobile Net is used with TensorFlow to perform flower-type classification. Accuracy results are obtained with values between 85 – 90%. Furthermore, in [11] modifying the MobileNetV2 architecture for face classification problems in a face verification system real-time called Mobile Face Net. The result is that the system can recognize faces at 24 ms with an accuracy of 99.28% and 93.05 %. From this research, it is known that the CNN Mobile Net architecture has a good performance in image recognition.

In a previous study, namely "MEDICAL ROBOT-CONTROLLED INTELLIGENT ASSISTIVE TECHNOLOGY" already installed an IMU sensor or inertial measurement unit sensor, 2D LiDAR sensor and 3D LiDAR sensor. So that in this study a visual-based object detection system will be built so that the covid robot can detect objects in order to improve the performance of the 2D LiDAR sensor [12]. Because this sensor requires a stable position to scan for the autonomous robot's navigation path.

II. Methodology

Method used in this study is a review of one of the existing research reports, where the results of the report will be taken to be used as a reference for research on existing Covid robots. In the covid robot research, this research has used LiDAR 3D and LiDAR 2D sensors as navigation mapping. This sensor plays an important role in the navigation of the COVID-19 autonomous robot. The use of this visual-based object detection method will be implemented in covid robot research so that the path of this autonomous robot can be even better. Therefore, in this paper, we focus on collecting data on pre-existing visual-based object detection methods to be used as a reference for research on Covid robots.

On the existing covid robots, in Fig. 1 below you can see the previously existing covid robots. In the picture, we can see that the necessary components have been installed, in the sense that this research is almost finished. The robot can also be seen, a 2D LiDAR sensor has been installed as a navigation sensor. In addition, it is also seen that the robot has a camera on the front of the robot. Therefore, with this object detection method can be implemented to improve the performance of the 2D LiDAR sensor.

The data collection of visual detection objects is carried out in the Bandung city area. The tools used are Lenovo Ideapad 320 laptops, Lenovo Ideapad 320 Webcam, and PyCharm IDE software. Digital image processing in this study aims to detect obstacles/objects. Fig. 2 describes the stages of object edge detection which are recorded in real-time by the camera. The image obtained is a frame of the surrounding environment in real-time. Images with RGB format will be converted into grayscale format first so that image calculations can be accelerated. Processing this image.

While in Fig. 3 is an example of an image input in the form of a box recorded using a webcam. The image color format will be changed from RGB to grayscale. This color format change is intended to simplify image calculations. If using the RGB format, an image consists of 3 color components, namely red, green, and blue. So that the image calculation process is carried out 3 times, namely the calculation of the red, green, and blue values. After the three values are calculated, the average value of each will be searched pixel. Meanwhile, when using the format grayscale, an image will be converted into black and white gradations with a value of 0 to 255. So the calculation process only takes place once. The following is a code snippet for the process of converting an RGB image to an image grayscale.

(a) (b)

Fig 1. Medical Robot-Controlled Intelligent Assistive Technology (MR-IAT) (a). Covid-19 robot, (b) 2D RPLiDAR sensor

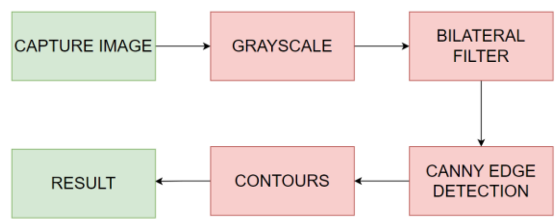


Fig 2. Image Processing Stages

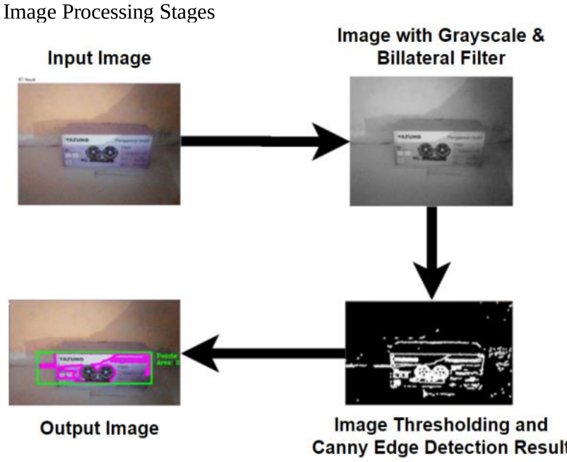


Fig 3. Image Processing Stage in the System

The image format grayscale will enter the stage of noise reduction using a bilateral filter. The use of bilateral filters aims to reduce noise in the image by keeping the edges of the image sharp. Because the edges of the image will be used to determine the characteristics of the image in the next method canny edge detector. After the filtered image stage preprocessing in image processing has been completed.

Furthermore, the image will enter the stage of feature extraction. At this stage, the characteristics of an image in the form of an obstacle object will be taken and processed with the help of the library OpenCV. The first method to be used in feature extraction is canny edge detection. This method is used to eliminate values pixel unwanted in images. The results of the method of canny edge detection are the edges of the detected image. The following is a program snippet of the process of canny edge detection. After the edge of the image is obtained, it will enter the phase of detection of the edge of the object/contour line. This stage is the stage for detecting obstacle objects. Obstacle objects are successfully detected if a purple line appears on the edge of the object contained in the input image. After that, the detected object will be wrapped in a bounding box green. In addition, the resulting image from this process will bring up the points and areas of the object itself. The following is a snippet of program code for the contour application process. When the image is successfully detected, a green square will appear as a bounding box for the detected object. Meanwhile, the light purple line is the outline of the object that has been detected by the system. In addition, a description of the points and areas of the detected object also appears.

The subprogram image processing will analyze the image acquired by the webcam. If the image information is obtained, then the image format conversion stage is carried out from RGB to grayscale and followed by filtering using a bilateral filter. The next stage is taking the characteristics of the object of detection using canny edge detection. Characteristics in the form of the edge of the obstacle object will enter the process of detecting the contour / outline of the object's edge. Fig. 4 describes the subprogram flowchart image processing.

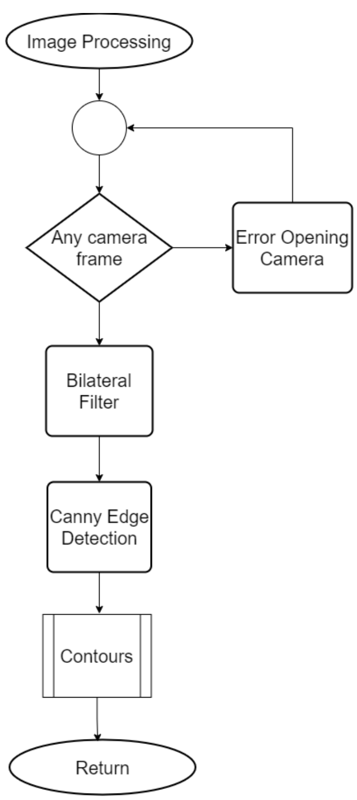
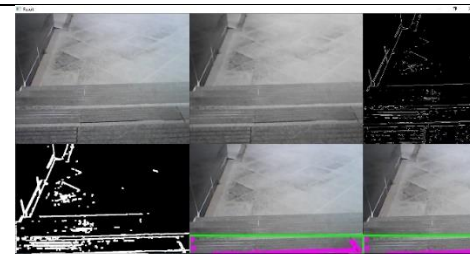
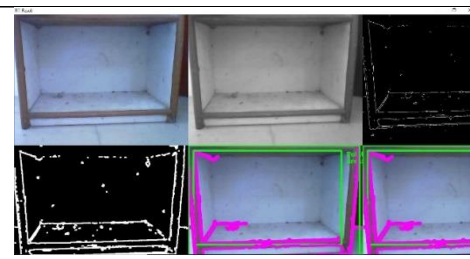
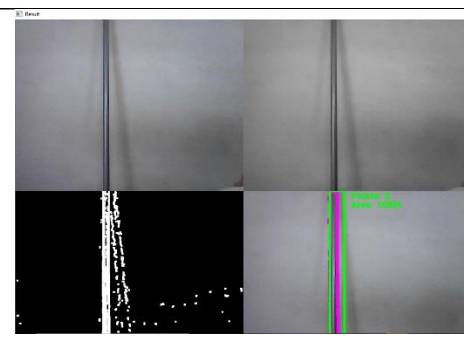
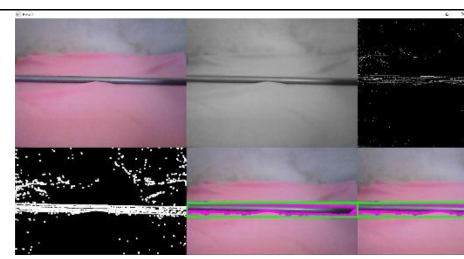


Fig 4. Image Processing

III. Results and Discussion

In this results section, observation and analysis data is displayed on the effect of light intensity on the object detection testing process using the Lenovo Ideapad 320 laptop webcam camera and testing the object detection distance.

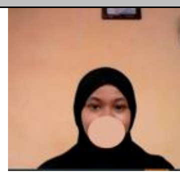
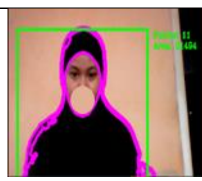
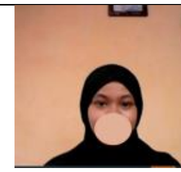
TABLE I
THE RESULTS OF THE DETECTION OF 4 GROUPS OF OBJECTS

No	Name	Object
1	Stair	
2	Table	
3	Pole	
4	Speed Bump	

Light intensity is the main factor that influences the image processing process. The effect of changes in light intensity can affect changes in values pixel in an image. Observational data for each value of light intensity is observed with the aim of being a large reference for the tolerance value of the light intensity of the environment around the object of detection. Object testing is divided into 2, namely testing people objects and testing objects in closed spaces.

In the human object test, the light intensity tolerance test on the human object aims to determine the value of light intensity that can still be received by the camera to be able to detect people. In this experiment, 7 samples of object detection data were used in the form of people with a distance between people and the camera as far as 50cm. Table 2 shows the observational data on the effect of changes in light intensity on the object detection process.

TABLE II
OBSERVATION DATA OF LIGHT INTENSITY ON PEOPLE OBJECTS

Data	Image Edge	Detection Result	Light Intensity (LUX)
1			24 (X)
Data	Image Edge	Detection Result	Light Intensity (LUX)
Data	Image Edge	Detection Result	Light Intensity (LUX)
2			32 (√)
3			42 (√)
4			56 (√)
5			66 (√)
Data	Image Edge	Detection Result	Light Intensity (LUX)
6			90 (√)
7			100 (X)

Analysis of observational data in Table 2 shows that the effect of light intensity that is not homogeneous greatly affects the success of detection. Experiments with light intensities of 24 LUX and 100 LUX show that the camera cannot distinguish people from surrounding objects. Detection failure is caused because the light intensity is able to increase or decrease the color intensity of the image, so the value of a pixel in the image grayscale cannot be detected properly. In this experiment, it was found that the intensity of 24 LUX and 114 LUX is the boundary between the detected object and the undetectable object. Experiments 2 to 6 resulted in objects being detected in accordance with the outline of the object, with light intensity varying from 32 LUX, 42 LUX, 56 LUX, 66 LUX, and 90 LUX. So it can be concluded that to be able to detect obstacle objects properly, the light intensity must be around 32 LUX to 90 LUX.

In object testing, the light intensity tolerance test on human objects aims to determine the value of light intensity that can still be received by the camera to be able to detect objects. In this experiment, 6 samples of object detection data were used in the form of people with a distance between objects and the camera as far as 50cm. Table 3 shows the observational data on the effect of changes in light intensity on the object detection process.

TABLE III
OBSERVATION DATA OF LIGHT INTENSITY ON OBJECTS

Data	Image Edge	Detection Result	Light Intensity (LUX)
1			15 (X)
2			58 (√)
3			74 (√)
4			102 (√)
Data	Image Edge	Detection Result	Light Intensity

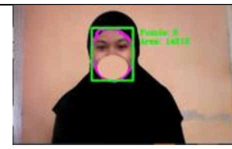
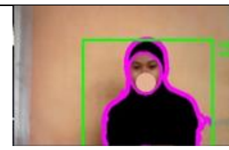
			(LUX)
Data	Image Edge	Detection Result	Light Intensity (LUX)
5			135 (✓)
6			160 (X)

Analysis of observational data in Table 3 shows that the effect of inhomogeneous light intensity greatly affects the success of detection. Experiments with light intensities of 15 LUX and 160 LUX showed that the camera could not distinguish objects from surrounding objects. Detection failure is caused because the light intensity is able to increase or decrease the color intensity of the image, so that the value of pixel the image grayscale cannot be detected properly. In this experiment, it was found that the intensity of 15 LUX and 160 LUX is the boundary between the detected object and the undetectable object. Experiments 2 to 5 resulted in the object being detected according to the object's outline, with light intensity varying from 58 LUX, 74 LUX, 102 LUX and 135 LUX. So it can be concluded that to be able to detect obstacle objects properly, the light intensity must be around 58 LUX to 135 LUX.

The camera sensor test data aims to find out how much the minimum and maximum distance of objects can still be detected by the camera. In this experiment, various light intensity values will be combined in the range tolerance that has been obtained in the previous experiment. Object testing is divided into 2, namely objects of people and objects.

In testing people objects, testing object detection using a camera is carried out to determine the success of detecting people with an image processing process that has been designed. The data to be processed is the closest and furthest distances that can still be received by the camera to recognize people's objects. The experiment was carried out 5 times with different environmental light intensity values. Table 4 shows the results of observational data in the form of maximum and minimum distances for object detection of people.

TABLE IV
DISTANCE OBSERVATION DATA

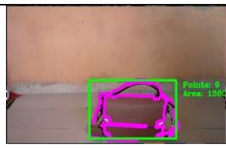
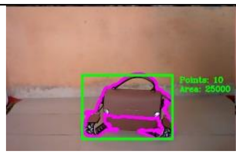
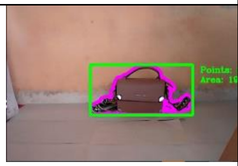
Data	Detection Result	Light Intensity (LUX)	Distance (cm)	
			Nearby	Farthest
1		32	16	115
2		42	19	140
3		56	18	139
4		66	16	142
5		90	17	151

Analysis of object detection distance observation data using a camera is the development of experimental analysis of the effect of light intensity on the success of detecting an object. The data in Table 4 lead to the conclusion that the shortest distance allowed is 19 cm from the object to the camera and the furthest distance allowed 115 cm in the range of light intensity that has been determined based on Table 2. The large tolerance LUX of light intensity by 32 to 90 LUX gain range detection distance from 19 cm to 115 cm.

In object testing, object detection testing using a camera is carried out to determine the success of object detection with an image processing process that has been designed. The data to be processed is the closest and furthest distances that can still be received by the camera to recognize people's objects. The experiment was carried out 4 times with different environmental light intensity values. Table 5 shows the results of observational data in the form of maximum and minimum object detection.

TABLE IV
DISTANCE OBSERVATION DATA

Data	Detection Result	Light Intensity (LUX)	Distance (cm)	
			Nearby	Farthest
1		58	20	94

2		74	20	89
3		102	30	95
4		130	30	95

Analysis of object detection distance observation data using a camera is an experimental analysis of the effect of light intensity on the success of detecting an object. The data in Table 5 concludes that the closest permissible distance is 20 cm from the object person to the camera and the farthest distance allowed is 95 cm in range the light intensity that has been determined based on Table 2, the tolerance for light intensity is 58 LUX to 130 LUX to get the range distance detection from 20 cm up to 95 cm.

Analysis of the effect of light intensity tolerance on the range of detection object distances concludes that light intensity does not affect the reading of the farthest and closest distances to the detection object. The data in Table 5 shows that with varying light intensities, the farthest and closest distances from the detection object choose values that are not much different from each other.

IV. Conclusions

The detection process is able to recognize obstacles in a light intensity range of 32 LUX to 90 LUX for people and a light range of 58 LUX to 130 LUX for objects. Then, the closest allowed distance is 19 cm from the object person to the camera and the farthest distance allowed is 115 cm in range of the predetermined light intensity. The closest distance allowed is 20 cm from the object person to the camera and the farthest distance allowed is 95 cm in the range of predetermined light intensity. With a large light intensity tolerance of 58 LUX to 130 LUX, ranges the detection distance from 20 cm to 95 cm. Analysis of the effect of light intensity tolerance on a range of the detection object's distance concludes that the light intensity does not affect the reading of the farthest and closest distances to the detection object. Therefore, from the results that have been obtained, this method can detect obstacles, namely people and objects. So that this method allows it to be applied to autonomous robots that have navigation sensors, namely LiDAR sensors.

Acknowledgment

This research is mainly funded by the “Hibah Riset Kemendikbudristek” research program run by the Indonesian Ministry of Education, Culture, Research, and Technology and supported by Universitas Padjadjaran, Indonesia.

References

[1] A. A. Balkhair, “Covid-19 pandemic: A new chapter in the history of infectious diseases,” *Oman Med. J.*, vol. 35, no. 2, pp. 2–3, 2020.

[2] A. Turnip, G. M. Tampubolon, S. F. Ramadhan, A. V. Nugraha, A. Trisanto, and D. Novita. "Development of Medical Robot Covid-19 based 2D mapping LIDAR and IMU Sensors." In *2021 IEEE International Conference on Health, Instrumentation & Measurement, and Natural Sciences (InHeNce)*, *IEEE*, pp. 1-4, 2021.

[3] S. Robotic, “ScienceDirect Sanitizing Robotic Platform in in in in the Autonomous Autonomous Autonomous for COVID-19 Autonomous for COVID-19 COVID-19 for COVID-19.”

[4] T. Struyf, CC-19 D. T. A. Group, J. J. Deeks, J. Dinnes, Y. Takwoingi, C. Davenport, M. M. G. Leeflang, R. Spijker, L. Hooft, D. Emperador, J. Domen, S. R. A Horn, A. Van den Bruel, “care or hospital outpatient settings has COVID-19 (Review),” vol. 19, 2021.

[5] S. F. Ramadhan, M. Taufik, D. Novita, and A. Turnip. "Design of 2D LiDar-based indoor SLAM for medical robot Covid-19." In 2021 *International Conference on Artificial Intelligence and Mechatronics Systems (AIMS)*, *IEEE*, pp. 1-5, 2021.

[6] M. Matsugu, K. Mori, Y. Mitari, and Y. Kaneda, “Subject independent facial expression recognition with robust face detection using a convolutional neural network,” *Neural Networks*, vol. 16, no. 5–6, pp. 555–559, 2003.

[7] A. Turnip, D. E. Kusumandari, G. W. G. Arson, and D. Setiadikarunia. "Electric Wheelchair Controlled-Based EMG with Backpropagation Neural Network Classifier." *In Cyber Physical, Computer and Automation System*, pp. 149-155, 2021.

[8] S. Singh and F. Nasoz, “Facial Expression Recognition with Convolutional Neural Networks,” *2020 10th Annu. Comput. comm. Work. conf. CCWC 2020*, pp. 324–328, 2020.

[9] M. Sandler, A. Howard, M. Zhu, and A. Zhmoginov, “Sandler_MobileNetV2_Inverted_Residuals_CVPR_2018_paper.pdf,” pp. 4510–4520, 2018.

[10] N. R. Gavai, Y. A. Jakhade, S. A. Tribhuvan, and R. Bhattad, “MobileNets for flower classification using TensorFlow,” *2017 Int. conf. Big Data, IoT Data Science. BID 2017*, vol. 2018-January, pp. 154–158, 2018.

[11] S. Chen, Y. Liu, X. Gao, and Z. Han, “MobileFaceNets Efficient CNNs for Accurate Real-Time Face Verification on Mobile Devices,” vol. 2, pp. 428–438, 2018.

[12] I. R. Defi, S. Iskandar, S. Charismawati, A. Turnip, and D. Novita. "Healthcare Workers’ Point of View on Medical Robotics During COVID-19 Pandemic–A Scoping Review," *International Journal of General Medicine*, 15, 2022.