Artificial Neural Network Algorithm for Autonomous Vehicle Ultrasonic Multi-Sensor System

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***Abstract* - Autonomous vehicles are vehicles that run automatically without a driver. Therefore, the vehicle requires sensors to detect surrounding objects to avoid collisions with other objects or vehicles. A variety of sensors can be used to support the system. One of the sensors used is an ultrasonic sensor that has the reliability and robustness to various light conditions and radio waves, especially when compared to camera sensors, radar and lidar. The recent implementation of ultrasonic sensors in vehicles is limited as a parking guide, so it needs to be developed for further functions, considering that ultrasonic sonar technology has advanced with even greater detection and long distances range. Hence, as a continuation of previous research in ultrasonic sensor characteristics, this paper carries out the application of artificial neural network algorithms that get input in the form of signals that refer to the output signal from the ultrasonic sensors, which have already assembled into a multi-sensor, which is 8 (eight) ultrasonic sensors positioned around the vehicle, two sensors in the front, two sensors in the rear and four sensors in the right and left side of vehicle. The sensors and algorithms will support the autonomous vehicle system, where if the sensors detect the obstructive objects, the system will provide an output in the form of a decision to make the braking order, soft braking, turning left, turning right, or staying run straight when the front sensors do not detect a barrier object. This is done in anticipation of an accident and avoid a collision. Each condition and decision will be determined by which sensor detects the barrier object. Input and output will be simulated using the tool of artificial neural network algorithms, so as to get the most optimal weight and low error rate.**

Keywords—neural network, ultrasonics, autonomous vehicle

I. INTRODUCTION

Autonomous Vehicle is a vehicle that moves and runs automatically according to predetermined paths and destinations. On its way the vehicle may meet some objects and obstacles like other vehicles, pedestrians, or other objects such as portals and traffic officers. For this reason, sensors and systems are needed to be able to detect accurately, quickly, precisely, and smartly. However, the existence of objects around the vehicle can be dangerous for the object as well as for the vehicle itself, and may occurs the accident [1]. It is Including other vehicles in front and back of the vehicle, in running state or stop. Each condition requires different settings adjusting to the detected object. In terms of regulation, road managers have not yet been prepared for the implementation of this autonomous vehicle, although the issue and development of autonomous cars has been touted since the beginning of the last decade. The policy regarding specific pathways and the rules for their implementation have not declared significant progress [2].

Various sensors are offered to support the autonomous car system. There are Lidar system, Radar, GPS, Vision/Camera, Inertial Measurement Unit (IMU), and other with their advantages and limitations, as well as ultrasonic sensors which have recently been widely chosen and considered to their distance detection range capabilities and its robustness to weather conditions [3]. An ultrasonic sensor has detection range (*S*) by multiplying sound speed (*v*) to its travel time (*t*) and dividing it by two, indicates the echo of the signal.

$$S = \frac{v\ x\ t}{2} \tag{1}$$

Recently, the existing sensor system is limited to providing information or signals if there is an object detected and has not provided complete detection in the vehicle environment, both front, side and rear. As Medina only provide sensors on the front side, Silpha adds infra-red sensors on the back side and Marco also only provides sensors on the front side [4]–[8]. While the proposed sensor system can adapt dynamically to the speed of the vehicle, as well as providing braking action when there are objects in front of the vehicle, considering into the distance of the object behind the vehicle, which may be another vehicle that is speeding as well.

Object detection aims to provide information on the existence of objects that are around the vehicle by taking data from sensors according to the distance and the detected object [9]. The data is obtained through the existence of sensors / detectors located on each side of the vehicle (front, side, rear) integrated into one in a microcontroller by applying artificial neural networks in it with the back-propagation method. The sensor used is a series of ultrasonic sensors that have a long range with a detection capability of 10 meters. Luciano's design has a difference in terms of the use of intelligent system algorithms. He choose genetic algorithms as controllers and learning systems [10], [11]. While the proposed system adopts an artificial neural network algorithm.

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The advantages of this system, ultrasonic sensors can detect the presence of barrier objects on all sides of the vehicle so the system built using artificial neural network algorithms can make a decision to stop the vehicle by braking and also considering the existence of objects around the vehicle, and controlling the steer to turn left or right to avoid obstruction objects. The front and rear sensors are able to adapt to the speed of the vehicle, where the input voltage to the sensor will increase as well as the vehicle's speed, so that the sensor's detection range increases as well. It is done to save the energy absorbed [12], [13].

II. System Design

The study was designed using ultrasonic sensors arranged in an array to detect objects around the vehicle. Consists of a front sensor array, a side sensor array and a rear sensor array. Front and rear sensors use perpendicular arrays using Maxbotix 7383HXRL sensors, and side sensors use parabolic or hyperbolic arrays using 7380HXRL sensors [14]. These sensors have been tested for their characteristics, and the result has no far deviation compared to its data sheet given [13].

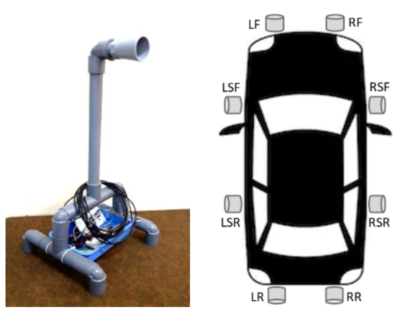

Fig. 1. Maxbotix Ultrasonic Sensor test and its placements

The range of the front sensors and rear sensors will adapt to speed. The faster of the vehicle's speed, the farther of the detection distance of the sensor, by adjusting the maximum capability of the ultrasonic sensor. During vehicle movement, if there is a barrier object detected, the system will do the braking by considering the presence of objects behind the vehicle.

The control system uses an artificial neural network algorithm that allows increasing the range of the detector when the vehicle's speed increases. The system design block diagram is in Fig. 2.

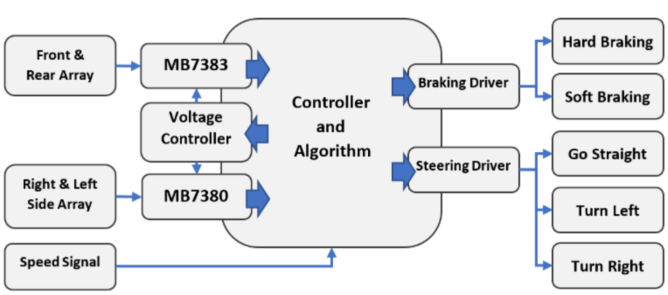

Fig. 2. Design of System

III. System Algorithm

System algorithm designed as the vehicle action due to sensors detections. Fig. 3 shows how the system works.

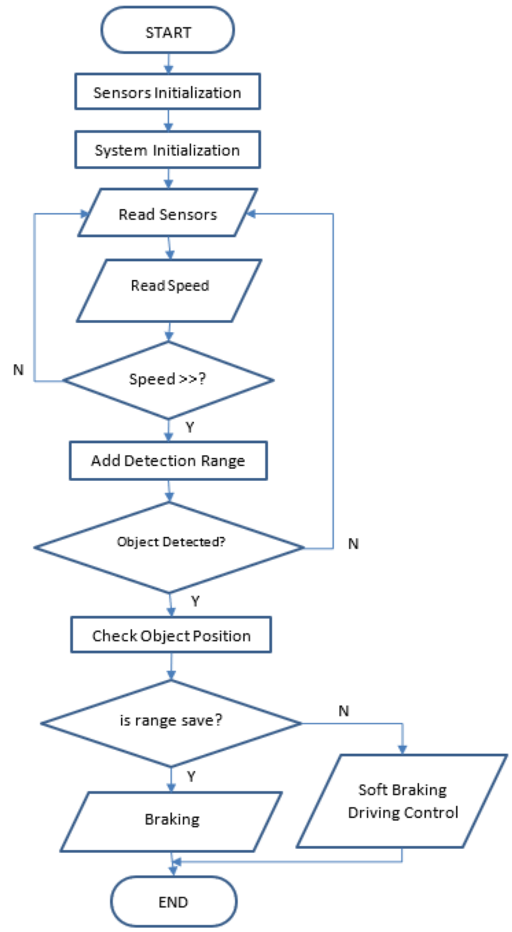

Fig. 3. Flow Diagram of system

This study uses an artificial neural network (ANN) algorithm as many of the previous researchers recommendation, considering that the algorithm is suitable for the application of barrier object avoidance systems in autonomous vehicles [5]–[8], [15]–[18].

Ultrasonic sensor as input is designed consisting of:

1. Front left sensor (LF)
2. Right front sensor (RF)
3. Left rear sensor (LR)
4. Right rear sensor (RR)
5. Front left side sensor (LSF)
6. Rear left side sensor (LSR)
7. Front right side sensor (RSF)
8. Rear right side sensor (RSR)

The variations of input can be $2^8 = 256$ conditions. This condition obtained from the normalization of the data of each sensor in detecting the distance of the object using the method of labeling - one hot encoding.

TABLE I. SAMPLE OF INPUT DATA BEFORE NORMALIZATION

LF	950	695	950	920	950	73	950	326	950	204	950	595	950	697	950	929	950	900	950	868	950	695	950	680
RF	174	909	950	950	542	481	950	950	869	784	950	950	292	781	950	950	622	577	950	950	888	819	950	950
LR	91	145	950	950	950	950	884	515	851	630	950	950	950	950	542	280	607	277	950	950	950	950	523	505
RR	950	950	859	845	344	526	627	731	751	110	950	950	950	950	950	950	950	950	625	53	378	390	800	765
LSF	115	85	389	348	358	165	74	332	399	227	450	450	450	450	450	450	450	450	450	450	450	450	450	450
LSR	325	339	409	158	279	445	121	146	78	69	450	450	450	450	450	450	450	450	450	450	450	450	450	450
RSF	247	342	284	120	426	442	247	462	457	481	450	450	450	450	450	450	450	450	450	450	450	450	450	450
RSR	450	450	450	450	450	450	450	450	450	450	432	417	138	201	200	99	226	318	109	357	144	377	473	156

TABLE I. TABLE II. SAMPLE OF INPUT DATA AFTER NORMALIZATION

LF	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1
RF	1	1	0	0	1	1	0	0	1	1	0	0	1	1	0	0	1	1	0	0	1	1	0	0
LR	1	1	0	0	0	0	1	1	1	1	0	0	0	0	1	1	1	1	0	0	0	0	1	1
RR	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	1	1	1	1	1	1
LSF	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
LSR	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
RSF	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
RSR	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1

TABLE II. TABLE III. INPUT VARIATIONS

Variation	LF	RF	LR	RR	LSF	LSR	RSF	RSR
0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	1
2	0	0	0	0	0	0	1	0
3	0	0	0	0	0	0	1	1
4	0	0	0	0	0	1	0	0
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
254	1	1	1	1	1	1	1	0
255	1	1	1	1	1	1	1	1

Output conditions are determined as follows:
1. Stop/Braking (S/B)
2. Soft braking (SB)
3. Turn left (TL)
4. Turn right (TR)
5. Going straight (GO)

By using the one hot encoding method, the OUTPUT logic condition stops (10000), soft braking (01000), turn left (00100), turn right (00010) and go straight (00001).

TABLE III. TABLE IV. SAMPLE OF INPUT AND TARGET

LF	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	INPUTS
RF	0	0	1	1	0	0	1	1	0	0	1	1	0	0	1	1	0	0	1	1	0	0	1	1	
LR	1	1	1	1	0	0	0	0	1	1	1	1	0	0	0	0	1	1	1	1	0	0	0	0	
RR	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	1	1	1	1	
LSF	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	
LSR	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
RSF	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
RSR	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
S/B	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	TARGETS
SB	0	0	0	1	0	0	0	1	0	0	0	1	0	0	0	0	0	0	1	1	0	0	1	1	
TL	0	0	1	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	
TR	0	1	0	0	0	1	0	0	0	1	0	0	0	1	0	0	0	1	0	0	0	1	0	0	
GO	1	0	0	0	1	0	0	0	1	0	0	0	1	0	0	0	1	0	0	0	1	0	0	0	

The hidden layer is determined to 27 conditions adopted from requirements of outputs. For learning purposes, each network is weighted by certain activation functions, from the input to the hidden layer and from the hidden layer to the output by the feed-forward method. Then the weight of the results of the learning is evaluated again from the output to the hidden layer and the hidden layer to the input using the back-propagation method. Every network has formula shown in (2).

$$y = \sum_{n=1}^{n} x.w + b \tag{2}$$

Where y is the output of the ANN, x is an input value, w is weight of the network, and b is bias.

The design of neural network algorithms is shown in Fig. 4.

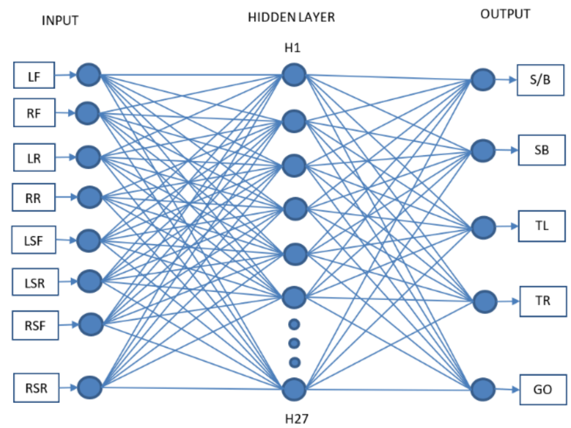

Fig. 4. Neural Network Algorithm Design

IV. SYSTEM TESTING

Testing of artificial neural network models with the backpropagation method is performed using Matlab software simulation. The simulation is adjusted to two system designs which one has 8 (eight) inputs, 27 hidden layers and 5 (five) outputs as configured in Fig. 5, and the other one is with10 hidden layers added (Fig. 6)

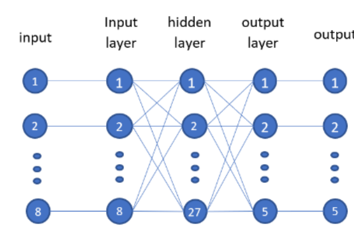

Fig. 5. System network design 1

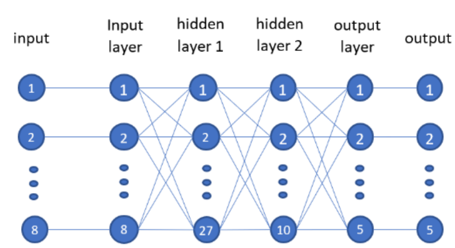

Fig. 6. System network design 2 with 10 hidden layers added

V. RESULTS

The iteration given in this test is 10,000 epochs, with a minimum gradient of 1.10^{-9}. After reaching the $10{,}000^{th}$ iteration, in about 16 seconds, the graphical results shown in Figs. 7-9. The simulation results show that the comparison of targets and outputs almost coincide in about 0.93 with single hidden layer, and in about 0.95 with double hidden layers, assuming that if the iteration is continued with a higher epoch value, it will get the results of the target-output comparison coincide more perfectly, which indicates a smaller error.

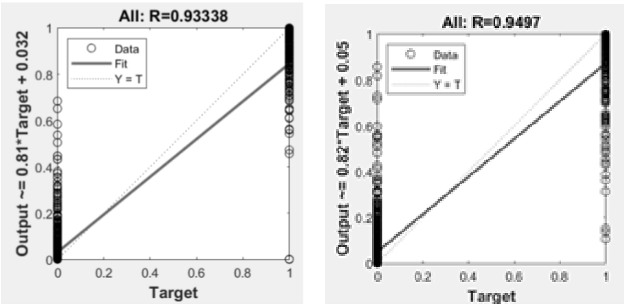

Fig. 7. Regression result of system testing of network 1 and 2

The grey line in both image of fig. 7 denote the ideal result of system network, where target and output results are in the same value. So the black lines show us that there are a little deferences between targets and outputs. It means the little deviation of both result lines.

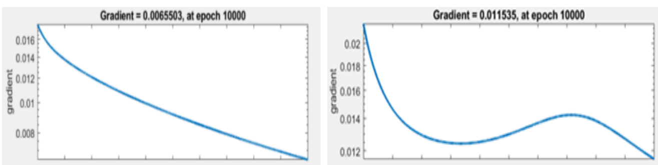

Fig. 8. Gradient graph of system testing of network 1 and 2

The curve of both graphs in fig. 8 shows that the gradient of network 1 is more linear than network 2. It describes the linearity of the network 1 reachment.

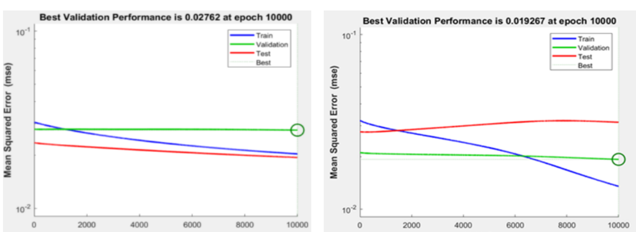

Fig. 9. Validation and MSE of system testing of network 1 and 2

A well-trained ANN should have a very low MSE at the end of the training phase, which in this training, equals to 0.02762 for network 1 and 0.0019267 for network 2. The meaning of MSE being very small (close to zero) is that the desired outputs and the ANN's outputs for the training set have become very close to each other.

VI. Conclusions

Ultrasonic sensors of Maxbotix MB7383 and MB7380 chosen in the autonomous vehicle system due to its reliability in detecting objects, especially its long range detection and its resistance to various lighting conditions, smoke, fog or rain. These sensors can be arranged in series or parallel to get the configuration of multipoint detectors on an autonomous vehicle. Artificial neural network algorithm is very possible to be recommended in the implementation of an autonomous vehicle to coordinate the input and output provided and process the data according to the learning system applied, in this case the back-propagation method. The near result value of regression to be one indicates good system performances.

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References

[1] Q. Long, Q. Xie, S. Mita, K. Ishimaru, and N. Shirai, "A Real-time Dense Stereo Matching Method for Critical Environment Sensing in Autonomous Driving," *2014 17th IEEE Int. Conf. Intell. Transp. Syst. ITSC 2014*, no. iv, pp. 853–860, 2014.

[2] A. Faisal, T. Yigitcanlar, M. Kamruzzaman, and G. Currie, "Understanding Autonomous Vehicles: A Systematic Literature Review on Capability, Impact, Planning and Policy," *J. Transp. Land Use*, vol. 12, no. 1, pp. 45–72, 2019.

[3] S. J. Babak, S. A. Hussain, B. Karakas, and S. Cetin, "Control of Autonomous Ground Vehicles: A Brief Technical Review," *IOP Conf. Ser. Mater. Sci. Eng.*, vol. 224, no. 1, 2017.

[4] J. P. D, P. Venugopal, and R. P. N, "Adaptive Cruise Control using Ultrasonic Sensor," vol. 8, no. 3, pp. 15949–15960, 2016.

[5] M. C. De Simone, Z. B. Rivera, and D. Guida, "Obstacle Avoidance System for Unmanned Ground Vehicles by Using Ultrasonic Sensors," *Machines*, vol. 6, no. 2, 2018.

[6] S. Sugathan, B. V. Sowmya Shree, M. R. Warrier, and C. M. Vidhyapathi, "Collision Avoidance using Neural Networks," *IOP Conf. Ser. Mater. Sci. Eng.*, vol. 263, no. 5, 2017.

[7] G. Farias *et al.*, "A Neural Network Approach for Building an Obstacle Detection Model by Fusion of Proximity Sensors Data," *Sensors (Switzerland)*, vol. 18, no. 3, 2018.

[8] A. Medina-Santiago, J. L. Camas-Anzueto, J. A. Vazquez-Feijoo, H. R. Hernández-De León, and R. Mota-Grajales, "Neural Control System in Obstacle Avoidance in Mobile Robots using Ultrasonic Sensors," *J. Appl. Res. Technol.*, vol. 12, no. 1, pp. 104–110, 2014.

[9] J. Park, Y. Je, H. Lee, and W. Moon, "Design of An Ultrasonic Sensor for Measuring Distance and Detecting Obstacles," *Ultrasonics*, vol. 50, no. 3, pp. 340–346, 2010.

[10] L. Alonso, V. Milanés, C. Torre-Ferrero, J. Godoy, J. P. Oria, and T. de Pedro, "Ultrasonic Sensors in Urban Traffic Driving-aid Systems," *Sensors*, vol. 11, no. 1, pp. 661–673, 2011.

[11] L. Alonso *et al.*, "Genetically Tuned Controller of an Adaptive Cruise Control for Urban Traffic Based on Ultrasounds," pp. 479–485, 2010.

[12] E. N. Budisusila, S. Arttini, D. Prasetyowati, B. Y. Suprapto, and Z. Nawawi, "Review and Design of Environmental Smart Detector for Autonomous Vehicle in Urban Traffic," *Aip Icon3E 2019 Uthm*, vol. 020008, no. November, 2019.

[13] E. N. Budisusila, "Pengujian Sensor Ultrasonik Maxbotix MB7383 untuk Kendaraan Otonom (Autonomous Vehicle)," 2019.

[14] Maxbotix, "HRXL-MaxSonar ® - WR ™ Series," 2012.

[15] R. Gutierrez-Osuna, J. A. Janet, and R. C. Luo, "Modeling of Ultrasonic Range Sensors for Localization of Autonomous Mobile Robots," *IEEE Trans. Ind. Electron.*, vol. 45, no. 4, pp. 654–662, 1998.

[16] H. J. Vishnukumar, "Machine Learning and Deep Neural Network – Artificial Intelligence Core for Lab and Real-World Test and Validation for ADAS and Autonomous Vehicles," *Intell. Syst. Conf. London, UK*, no. September, pp. 714–721, 2017.

[17] M. S. Obaidat, H. Khalid, and B. Sadoun, "Ultrasonic Transducer Characterization by Neural Networks," *Inf. Sci. (Ny).*, vol. 107, no. 1–4, pp. 195–215, 1998.

[18] G. A. Santiago and M. Favre, "Analysis and Evaluation of Recurrent Neural Networks in Autonomous Vehicles," 2017.