Improving Obstacle Detection of Automated Guided Vehicles via Analysis of Sonar and Infrared Sensors Output

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Abstract

Automated Guided Vehicles (AGVs) are machines used in aiding the process of conveying materials from one point to another. AGVs are extremely useful in the materials handling process; hence, the reasoning behind their extremely wide usage in industries such as manufacturing, healthcare, pharmaceutical, etc. Due to the wide usage of AGVs, researchers continue to seek solutions to further improve the performance of these machines. One of the areas that could be further improved is the obstacle detection module of AGVs since they are increasingly being implemented in highly congested environments. This research investigates how the speed of the AGV and the type of obstacle it comes in contact with could affect the distances at which the sonar and infrared sensors detect obstacles. The Arduino Uno starter kit with a DC 6V 4-wheel robot smart car chassis kit was utilized to model a small-scale AGV. Using the Arduino integrated development environment, the assembly was programmed such that obstacle detection of objects was performed. Analysis of Variance (ANOVA) was carried out to evaluate differences in distances recorded by the prototype assembly when the sonar sensor was connected versus when the infrared sensor was connected. The research concludes that sonar sensor readings are not significantly different while infrared sensor readings are significantly different.

Keywords
Automated Guided Vehicles, Obstacle Detection, Industrial Engineering, Analysis of variance

Introduction

Automated Guided Vehicles, popularly called AGVs, are used to aid the process of conveying materials from one point to another. Rather than having to rely heavily on conveyor systems, these machines make it easy so that materials can be moved over several distances without the need for long manufacturing lines in the day-to-day movement of raw materials or finished products. The roles these machines have played in the movement of materials since 1953 when they were first introduced cannot be under-estimated. The first AGV built in 1953 by Barrett Electronics Corporation was designed and used as a modified tow truck which navigated from one point to another by following a wire on the ground (Hill & Jew, 2013).

In the year 1973, Volvo Kalmar in Sweden decided to do away with the conventional slat conveyor system and replaced the system with 280 computer-controlled assemblies of AGVs which was used in the production of the Volvo 164 model (Hill & Jew, 2013). This led to the further development of the AGVs by the mid-1970s known as the unit load AGVs which are battery powered drive units that are capable of performing several functions. Non-wire guidance systems such as laser and inertial guidance methods were introduced in the late 1980's ("AGV Knowledge Center," n.d.). Laser guidance refers to a navigation system used in guiding a vehicle towards its target through the use of laser beams while inertial guidance refers to a navigation aid that uses computer motion and rotation sensors to continuously calculate the position, orientation and velocity of a moving object without the need for external references ("Inertial Navigation System," n.d.).

Today, these AGVs are capable of performing the majority of the material handling processes that are being done by humans and are capable of working for longer periods than humans. Their importance to the material handling process cannot be overemphasized as they are widely used in several industries (e.g., manufacturing, transportation, healthcare, pharmaceutical, retail, etc.) to enhance the efficiency of the materials handling process. While there are several aspects of an AGV that could be studied, there remains a drive for the successful and safe navigation from one point to another. One key element is that the AGV needs to be able to detect obstacles that are in its path so as to plan the best route to avoid collision with the obstacles. Elsewise, these collisions could result in injuries to people, damage to the vehicles and subsequent losses and/or possible damage to products and materials being transported. This research investigates how data obtained during the operation of AGVs with sonar and optical sensors could be analyzed to reveal how they best respond to surfaces; thereby enhancing our understanding of the surface types that minimizes collision in the process of operation.

2.1. Sonar Sensor Techniques

Huang, Supaongprapa, Terakura, Wang, Ohnishi, & Sugie, (1999) discussed visual sensors as one of the most popular sensors being used for mobile robots but the difficulties that arise when an object does not exist in the visual field of cameras was highlighted. Huang et al. (1999) modeled a sonar system which consisted of four parts namely; a three microphone omni-directional unit, a digital signal processor (DSP), a personal computer and a mobile robot base. An obstacle of about 0.47m height was placed between the initial position of the robot and the sound source at the goal in such a way that the sound source direction was not obstructed. Results obtained indicated that the robot could accurately localize the sound while avoiding the obstacle using the sonar system and moving closer towards the sound source. An additional experiment was conducted by the authors to block the sound source such that it was invisible to the robot and realign the path in a way that the direct path which was available in the first experiment was no longer available. This experiment also revealed that the robot also was able to localize the sound but the accuracy was lower than what was obtained with a direct path.

According to research carried out on an advanced prototype Computer Controlled Power Wheelchair Navigation System (CCPWNS) by Del Castillo, Skaar, Cardenas, & Fehr, (2006), ultrasound range sensing has been in use since the mid 80s to generate simple data. In the research, the risk of using sonar was highlighted in that there is no guarantee that objects detected within the cone correspond to an object that lies in front of the plane of the transducer while using a simple time of flight sensing. This flaw did not prevent the use of the technique since it has advantages one of which is the consistency of the data output.

2.2. Laser Technique & Simulation

Martínez-Barberá, & Herrero-Pérez, (2010) describe the navigation system of a flexible custom modified AGV (i.e., an OMG 808 FS commercial fork-lift truck) which was modeled into four phases namely; perception, planner, navigation and controller modules. Navigation and guidance which allowed the vehicle to follow a route was achieved by a laser system localization technique.

In research by Berman, Schechtman, & Edan (2009), the authors analyzed AGV operation parameters such as idle time, utilization, empty travel times and number required for meeting production demands. The authors used stand-alone sub module evaluation method where the AGV functionality was divided into three main sub modules namely system management, navigation and load transfer. An evaluation of the system was then performed using the ARENA® simulation software and weighted summations of multiple attributes were compared for various manufacturing system sizes, AGV numbers and production rates. The research concluded that fuzzy dispatching performs as well or better than the other tested algorithms and the importance of fuzzy dispatching becomes significant in high volume systems having high production rates.

2.3. Statement of the Problem

As established in the literature review section, previous researchers have used a host of sensors namely visual, optical, laser and so on as techniques to aid AGVs in obstacle detection. A lot of investment goes into developing new sensor technologies that is capable of detecting obstacles accurately but there has been limited research performed in the area of analyzing how these AGVs through attached sensors respond to different surfaces and speed. Consequently, this research seeks to investigate the extent to which sonar and infrared sensors could aid obstacle detection in AGVs by performing a full analysis of the data output of these two sensors to show the strengths of each sensor and how they could possibly be combined to aid AGVs in obstacle detection while improving the overall performance of these techniques.

2.4. Research Objectives

The main objective of this research is to establish the extent to which speed and the type of surface influence the distance at which sonar and infrared sensors detect obstacles in AGVs in order to improve navigation and minimize collisions.

This objective would be carried out by:
(1) varying the factors at different levels to reveal inferences that could be drawn to further optimize the performance of these AGVs
(2) analyzing the data output based on the factors selected to draw conclusions based on findings.

3.0. Methodology

A 4-wheeled smart car robot chassis kit was purchased and other components (Arduino Uno microcontroller board, Wicked Device motor shield, sonar and infrared sensors) were attached to form a complete robot AGV prototype shown in Figure 1 which was used to perform the experiment

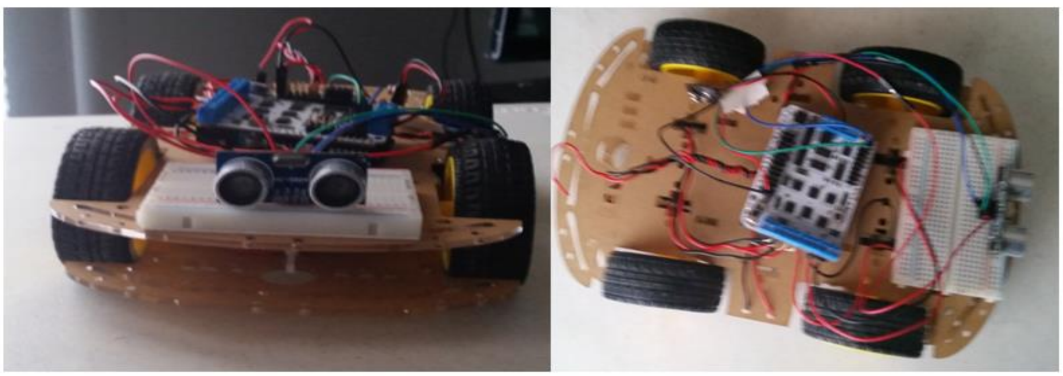

Figure 1. Complete robot AGV prototype (frontal & aerial view)

The AGV prototype was then made to operate while facing different types of obstacles placed in a straight line path of the prototype with the sonar and infrared sensors attached at different times as shown in figure 2. The Arduino; a microcontroller board has a serial monitor embedded with an integrated development environment (IDE) where distances detected by the sensors are displayed. Analysis of variance (ANOVA) was used to verify the effect of two factors; speed of the prototype and the types of obstacles that an AGV could possibly encounter during operation. Distance displayed by the serial monitor was selected as the response variable.

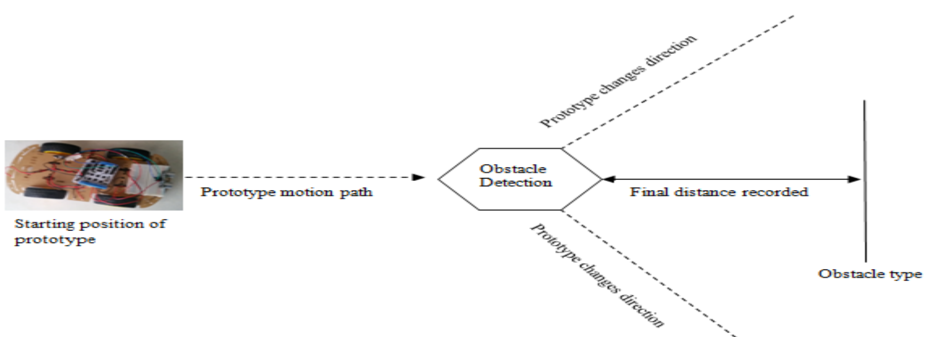

Figure 2. Overview of an experimental trial

The goal of the experiment is to find out the extent to which speed (factor 1) and obstacle type (factor 2) affect the distance at which the prototype detects obstacles and if interaction of these factors actually play a role in helping to maximize the distance at which the prototype detects obstacles thereby minimizing collisions. To evaluate the effect of these two factors, ANOVA of the distances recorded by the sonar and IR sensors were performed to nullify or verify our null and alternate hypotheses as shown by equations (1) - (6). The analysis was performed at 95% confidence interval (C.I.) on Minitab® and decisions were made based on the tabular output. The analysis was also subjected to Tukey test at 90 and 99% C.I. to make a sound decision.

The prototype was set at an initial distance from an obstacle type and was allowed to move in a straight line motion towards the obstacle. At some point during motion, the prototype detects the presence of the obstacle, stops and changes course of direction to the left or to the right depending on which path was free. The distance recorded was the distance at which the prototype detects an obstruction in it's path and stops. This procedure was repeated ten times for each obstacle type at each speed levels. The speed factor levels selected are 80, 90, 100, 110, and 120 (bytes/sec). while the obstacle type levels selected were plastic, wall, metal, human, wood, and empty carton. These speeds were selected due to the fact that they are speeds at which optimal performance of the prototype was observed and the obstacle types were selected due to the fact that they represent possible obstacle types a real AGV could encounter in its daily operation. The experiment was repeated ten times at each factor level combination of speed and obstacle type ultimately leading to a collection of three hundred data points that were subsequently analyzed. Since AGV speed levels were reported in bytes/sec and refer to the data acquisition and sending rate of the prototype. This speed could be related to a real AGV by checking the distance which the prototype covered over a specific time frame. For example, it took about 2.04 seconds to cover a distance of about 33cm; speed in terms of a real AGV would be about 33cm/2.04s = 16.176 cm/s which is about 0.53 ft /sec.

H_0: $\tau_{80}=\tau_{90}=\tau_{100}=\tau_{110}=\tau_{120} = 0$ (1)
H_1: $\tau_i \neq 0$ for at least one i value (2)
H_0: $\beta_{plastic}=\beta_{wall}=\beta_{metal}=\beta_{human}=\beta_{wood}=\beta_{emptycarton} = 0$ (3)
H_1: $\beta_j \neq 0$ for at least one j value (4)
H_0: $(\tau\beta)_{ij} = 0$ for all ij values (5)
H_1: $(\tau\beta)_{ij} \neq 0$ for at least one ij value, where i = speed and j = obstacle type (6)

Equation (1) is the null hypothesis which states that there is no significant difference in the distances at which obstacles are detected at different speeds while equation (2) is the alternative hypothesis. Equation (3) is the null hypothesis which says that there is no significant difference in the distances at which different obstacle types are detected while equation (4) is the alternative hypothesis. Equation (5) is the null hypothesis which says that there is no significant difference in the distances at which the prototype detects obstacles at different speeds and for different obstacle types while equation (6) is the alternative hypothesis. The statistical model represented by equation (7) is the model that was used for the experiment.

$$y_{ij} = \mu + \tau_i + \beta_j + \varepsilon_{ij} \quad (7)$$

4.0. ANOVA

Three hundred data points each were collected at the end of the experiment using both the sonar and the infrared sensors. The data was then analyzed using Minitab and the ANOVA outputs are shown in tables 1 and 2.

Table 1. Sonar sensor ANOVA for distance

Source	DF	Adj SS	Adj MS	F-value	P-value
Obstacle type	5	16.150	3.230	2.76	0.019
Speed	4	9.247	2.312	1.98	0.098
Obstacle type*Speed	20	18.233	0.912	0.78	0.737
Error	270	315.500	1.169		
Total	299	359.130			

At a significance level of 0.05, the p-value for obstacle type is less than 0.05 indicating that obstacle type as a factor has some level of significance in the readings that were obtained for the distance. The row which immediately follows obstacle type is speed and the p-value which is slightly higher than 0.05 indicates that there is a minimal level of significance. The next row shows the interaction between the obstacle type and speed which indicates a very high p-value and a conclusion was drawn that this interaction is not statistically significant.

Table 2. Infrared sensor ANOVA for distance

Source	DF	Adj SS	Adj MS	F-value	P-value
Obstacle type	5	20.35	4.070	3.56	0.004
Speed	4	87.73	21.933	19.18	0.000
Obstacle type*Speed	20	41.47	2.073	1.81	0.019
Error	270	308.70	1.143		
Total	299	458.25			

At a significance level of 0.05, the p-value for obstacle type is significantly less than 0.05, indicating that obstacle type has some level of significance. The next row which is the speed factor also has a p-value that is significantly less than 0.05. Based on this result as well, it was concluded that speed has some level of significance. The interaction of both factors presented in the third row also has a significant effect.

4.1. Tukey's test for sonar sensor data

Tukey test is a statistical method that allows for the comparison of differences among combinations of factor levels. This is usually done at specific C.I. to allow for more stringent or more relaxed evaluation. The research was conducted at 95% C.I. so the researchers used 90 and 99% C.I. as the comparative basis. At 95% C.I., Tukey's test result for sonar sensor distances shown in Figure 3 reveals that there are no differences in the means of both obstacle types and speed factors since all possible combinations have points that contain zero.

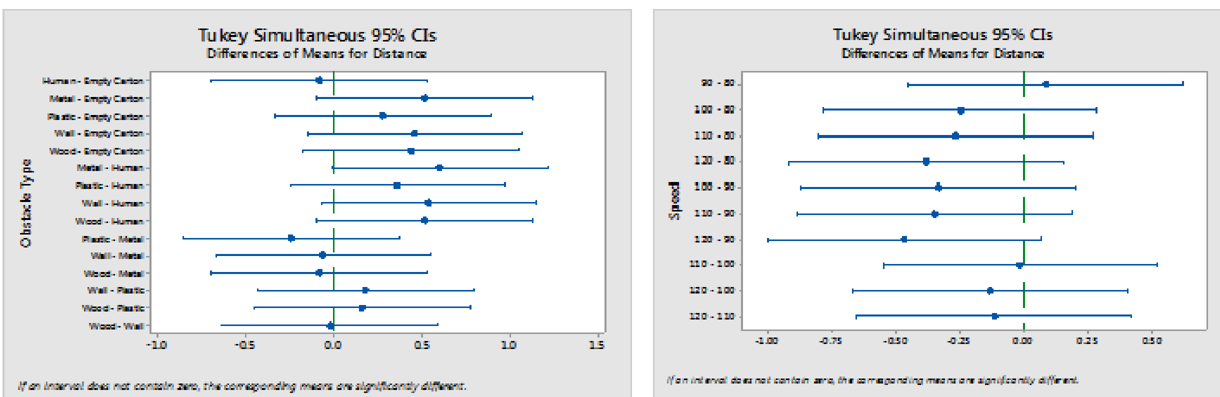

Figure 3. Tukey test for sonar sensor obstacle types and speed factors at 95% C.I.

Similarly, Figure 4 shows that at 90% C.I., Tukey's test result for sonar sensor distances reveal no differences in the means of both obstacle types and speed factors since all possible combinations have points that contain zero.

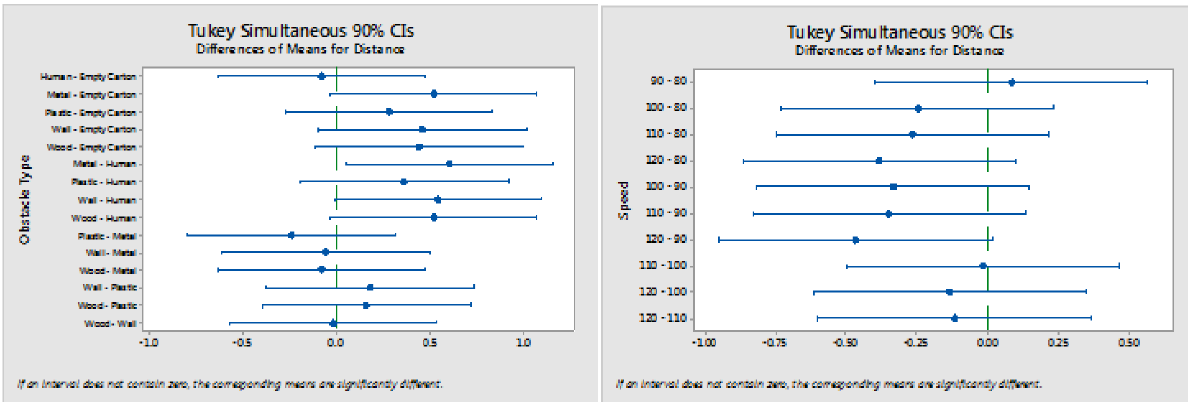

Figure 4. Tukey test for sonar sensor obstacle types and speed factors at 90% C.I.

Likewise, Figure 5 shows that at 99% C.I., Tukey's test result for sonar sensor distances reveal no differences in the means of both obstacle types and speed factors since all possible combinations have points that contain zero.

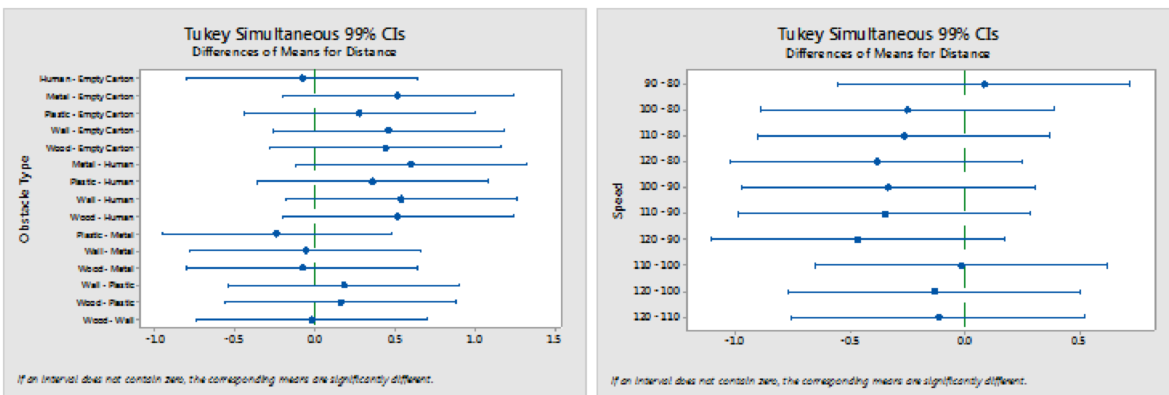

Figure 5. Tukey test for sonar sensor obstacle types and speed factors at 99% C.I.

4.2. Tukey's test for infrared sensor data

At 95% C.I., Tukey test result for infrared sensor distances shown in Figure 6 reveals that the means of different obstacle types are significant between metal and empty carton obstacle types as well as between metal and human obstacle types since they are the only ones that do not contain zero. However, significant differences in means can be observed for different speed factors.

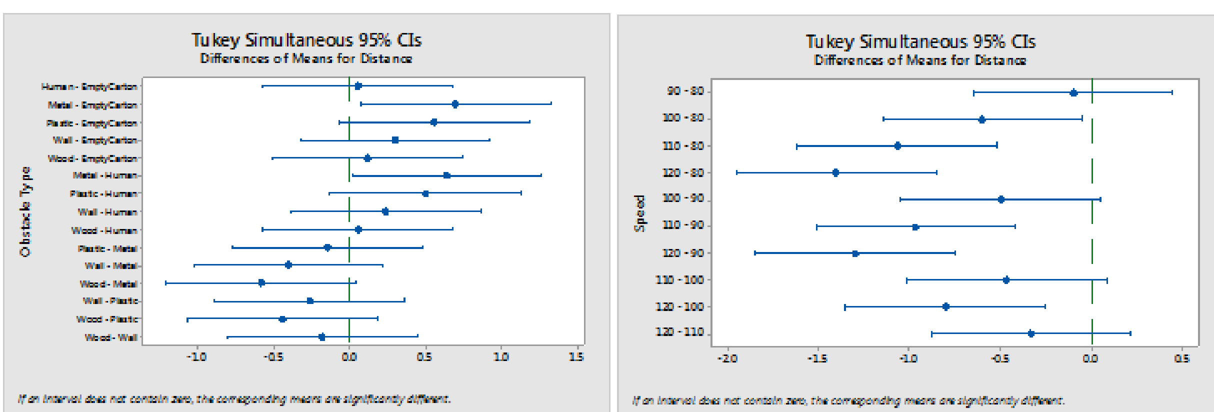

Figure 6. Tukey test for infrared sensor obstacle types and speed factors at 95% C.I.

At 90% C.I., Tukey test reveals some minimal significance in the means for different obstacle types shown in Figure 7 while speed still retains a high level of significance

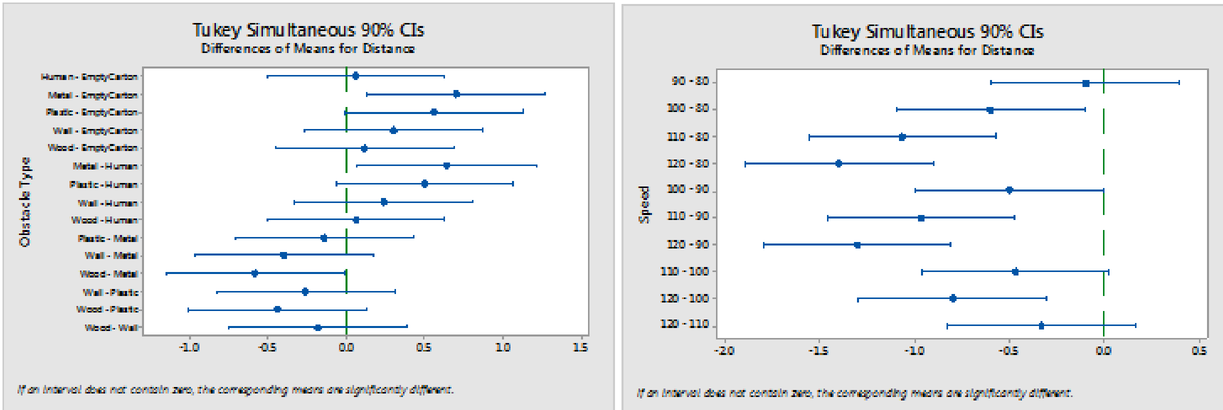

Figure 7. Tukey test for infrared sensor obstacle types and speed factors at 90% C.I.

However, at 99% C.I. shown in Figure 8, it can be observed that there is no significant difference in the means for obstacle types while speed retains some level of significance from one level to another.

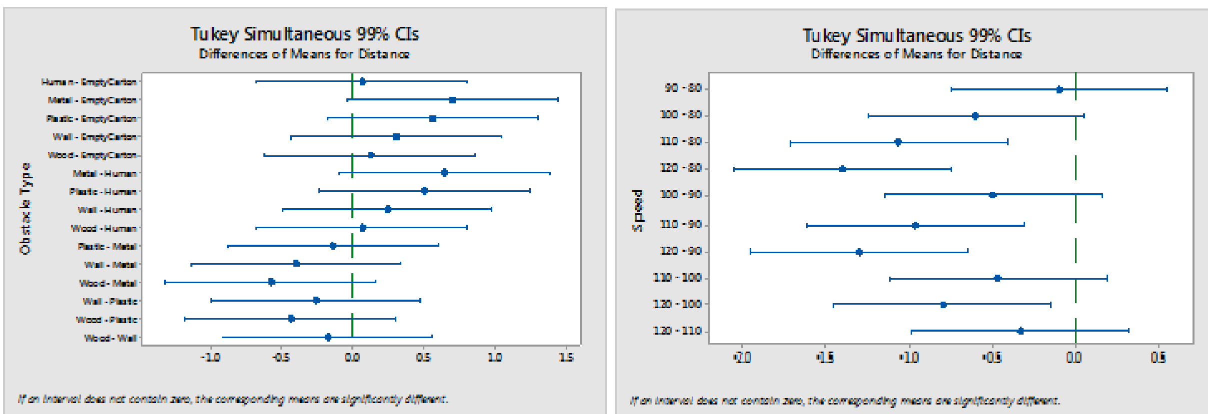

Figure 8. Tukey test for infrared sensor obstacle types and speed factors at 99% C.I.

5.0. Conclusion

After conducting the ANOVA test at a significance level of 0.05, it was concluded that the differences observed for different obstacle types were significant. A closer look at the result using Tukey's pairwise comparison at 90%, 95% and 99% C.I. revealed that differences were only observed between distances obtained for human and empty carton obstacle types at 90% C.I. However, since this test was carried out at a 95% C.I. and a corresponding comparison at 99% C.I. revealed no significant differences, the null hypothesis was rejected and a conclusion was drawn that the readings recorded from the sonar sensor is not impacted by the type of obstacles on the basis that we do not have enough statistical evidence to support the claim. The ANOVA table also revealed that the difference at different speed levels has some minimal significance since the p-value obtained was so close to 0.05 but Tukey's pairwise comparison at 90%, 95% and 99% C.I. revealed that there were no significant differences in the mean of the distances obtained. On this basis, the null hypothesis was also rejected and conclusion was drawn that the speed factor is not significant in the distances recorded by the sonar sensor. A final conclusion was drawn on the interaction effect based on the output from the ANOVA table which returned a significantly large p-value indicating that there is no significant interaction between our two factors that may affect the distances recorded.

Based on the ANOVA output, the tests conducted for the infrared sensor at a significance level of 0.05 revealed that the differences observed for different obstacle types were significant. A closer look at the result using Tukey's pairwise comparison at 90%, 95% and 99% C.I. revealed that significant differences could be observed at 90 & 95% C.I. while differences were insignificant at 99% C.I. Since this test was conducted at a significance level of 0.05 and the result was also verified using the Tukey's test, a conclusion was drawn that obstacle type affects the distances recorded by the AGV prototype while the infrared sensor was attached. Consequently, the null hypothesis was rejected and conclusion was drawn that obstacle type affects the distances recorded by the infrared sensor.

Likewise, a conclusion was drawn based on our ANOVA table that speed is also a significant factor. A comparison using Tukey's test revealed that significant differences were observed at 90%, 95% & 99% C.I. On this basis, a conclusion was drawn that we have strong statistical evidence to reject our null hypothesis and conclude that speed affects the distances recorded by the AGV prototype while the infrared sensor was attached. A final conclusion was drawn on the interaction effect based on the output from the ANOVA table which returned a low p-value indicating that there is some interaction between the two factors that may affect the distances recorded.

5.4. Recommendation

Based on the statistical tests performed on the sonar sensor readings, it is recommended that AGVs that have sonar sensors attached may be operated in the environments having the different obstacle types listed earlier and at speeds considered safe enough where these AGVs operate. The infrared sensor on the other hand shows significant differences in distances recorded at different speed levels and also when faced with different obstacle types. It is thereby recommended that this sensor should be used at low speeds which are considered safe and with the mindset that metal, plastic and wall surfaces return the highest average distances for this sensor type.

5.3. Future Work

This research could be extended further to real AGVs and the number of factors may be increased for the purpose of further analysis. Factors such as when the AGV operates in an area that is well lighted versus operating in an area of minimal to no lighting could also be considered. Data that has been collected in the course of this research may also be analyzed further to reveal relationships that could be deduced. The two sensors could also be combined to investigate the possibility of improving the distances at which obstacles are detected. Also a more complex path could be implemented since AGVs operate on a fixed and complex path.

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Biography

Ademola Abodunrin recently graduated with a Master of Engineering degree from the Industrial & Systems Engineering department at Morgan State University, Baltimore MD, USA. He earned his Bachelors in Mechanical Engineering from Lagos State University, Lagos, Nigeria. Most recently, he completed an internship with the Traffic

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