

# Algorithm for the Control of an Autonomous Excavator

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## Abstract

Population growth generate an increase in infrastructure, construction time is relatively high due to environmental conditions, operation times and building, for this reason is important to create alternatives that can provide solutions and can be implemented without any difficulty. In the current paper, it will going to present the implemented algorithm on a scale excavator, in order to perform work without the intervention of the human being. There are some factors that have to consider in order achieve an autonomous mobile vehicle, some of them are mobile tracking using sensor as encoders or with GPS (global position system) devises. Determine which objects are around using ultrasound sensors, laser, person identification and objects using computer vision in order to simplify the decisions of the mobil. The main contribution of this article is the application of an algorithm using Python software and low cost devises as ultrasound sensor for the development of the application.

**Keywords:** People identification, autonomous excavator, encoder, GPS, remote vision, neuronal network, Python.

## INTRODUCTION

Due to exponential, grow of population [1], the infrastructure expansion is very crucial, before being able to make a building it is important to appropriate the land on which it is going to be built. One of the more efficient ways to remove material in the land is using excavators, allowing to, reduce operation times, and increase the amount of material to remove in order to have a better performance in the construction process [2].

An excavator is a devise that works in a complex way it must be taken in account for the control device some variables, such as, localization, terrain altitude, amount of material to be removed and physics properties of the land, the last one is going to indicate the strength that the shovel have to apply in order to remove material [3].

An autonomous excavator can perform tasks without the intervention of the human being, allowing reducing operation cost the error and increase the devise operation times, to achieve the lowest error percent a high amount of devises must be used, these allow real time location of the vehicle and the identification of the environment [4].

There are different ways to identify objects that can be found around the excavator. One of the methods that allow measure distance is through ultrasound devises, these can be around the vehicle, these sensors work sending and receiving a signal that

travels at the speed of sound. Depending on the time, the signal takes to return an estimate of the distance can be made [5].

Is highly important to identify the position of an autonomous system, this allows the decision making for the device; generate coordinates on a space for the environment reconstruction. One of the ways to obtain the current position of a vehicle is using a GPS; a kalman filter can be implemented to achieve a better precision on the devise [6].

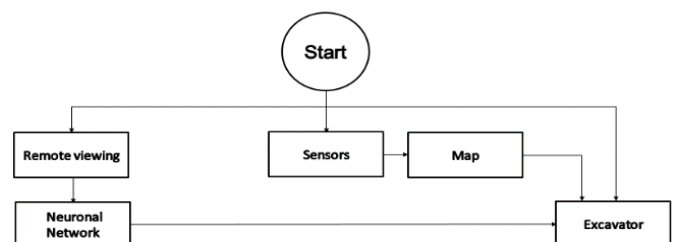
For the identification of different objects on the work area, the artificial intelligence concepts can be used, specifically neuronal networks, due to the high computational cost they require, it is better to implemented on a computer outside the work area. In the same way and as a security parameter, the errors produce by poorly functioning sensors can be reduce using neuronal networks [7].

The main objective of the work is achieve the implementation of an algorithm that allow the autonomous displacement of a scale excavator, which will allow the partial reconstruction of the environment, can perform the identification of people through a neural network and allow remote viewing on a computer, the excavator must be able to be handled manually and must be programmed in the Python language.

## METHODS AND MATERIALS.

The development is divide in three sections, the first one is going to realize the people identification using a neuronal network, the second one will allow the positioning of the vehicle and the last one will be in charge of the partial reconstruction of the environment.

In the figure 1, it can be seen the control block diagram for the excavator, this block diagram contemplates the entire operation of the system.



**Figure 1.** Block diagram.

As it can show the neuronal network is done through remote viewing, the ultrasound sensors are going to be charge of the reconstruction of the environment. The figure 2, illustrate the

sketch of the vehicle that will be used for the development of the application, in these figure it can be identify the different elements that the vehicle owns.

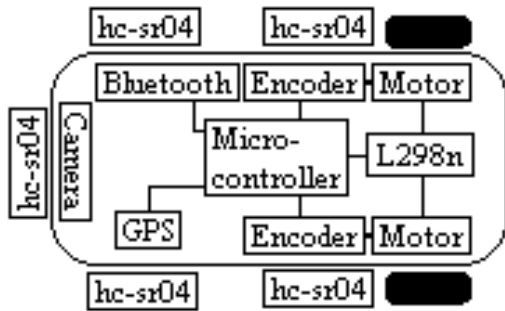


Figure 2. Car elements

### Kinematic model of the vehicle.

The figure 3 illustrate the design of a differential vehicle, where certain variables are declared such as, the tangential speeds of each wheels, the lineal speed and the size of the vehicle, and the diameter of each wheels, the x,y variables correspond to the coordinates of the vehicle in the space.

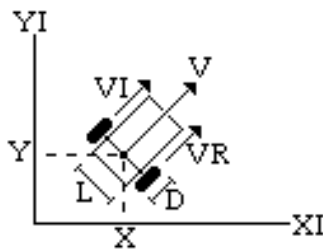


Figure 3. Kinematics model of a differential vehicle.

In the excavator development a differential model was taken into account, this kind of design allows the displacement in two dimension, and have parameters such as lineal tangential speed for the vehicle [8].

From the kinematic model, it can obtain equations (1) and(2):

$$V_L = W_R * r \quad (1)$$

$$V_R = W_L * r \quad (2)$$

The equations (1) and (2) allow to obtain the tangential speed of the wheels  $V_L$  and  $V_R$ ,  $r$  correspond to the wheels radius on the vehicle,  $W_L$  and  $W_R$  are the angular speed of the wheels, when (1) and (2) are replace on (3) and (4) it can be obtain the linear speed of the mobile [9].

$$V = \frac{V_R + V_L}{2} = \frac{(W_L + W_R) * r}{2} \quad (3)$$

$$W = \frac{V_R - V_L}{L} = \frac{(W_R - W_L)}{L} \quad (4)$$

For the implementation of the mobile robot with the current kinematics model, it will have p vector that containing the vehicle coordinates on the space and the orientation of it. In addition, the linear and angular speed must be consider, this kind of models only apply if the field is flat. By taking the model to a matrix form, it can obtain as a result the equation (5) [10].

$$\begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{\theta} \end{bmatrix} = \begin{bmatrix} \cos \theta & 0 \\ \sin \theta & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} V \\ W \end{bmatrix} \quad (5)$$

In order to calculate the inverse kinematics model obtain in (5) it must be use the pseudo inverse show in the equation (6). This can be obtain multiplying the transposed of the original matrix, applying the inverse in this operation and multiplying the total with the transposed, the equation (7) can be obtain as a result for applying the pseudo inverse.

$$A^+ = (A^t A)^{-1} A^t \quad (6)$$

$$\begin{bmatrix} V \\ W \end{bmatrix} = \begin{bmatrix} -\sin \theta & \cos \theta & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{\theta} \end{bmatrix} \quad (7)$$

The figure 4, show the solutions for the model equation, using the computational tool Matlab Simulink®, based on the equation (5). This equation, represent the kinematics model of a differential robot and can realize a simulation to illustrate the corresponding working of the model using different types of signals entries for each wheels.

Integrating the equations obtained in (5), the position equations (8), (9) and (10) can be obtained:

$$X(t) = x_o + \int_0^t v(t) \cos(\theta(t)) dt \quad (8)$$

$$Y(t) = y_o + \int_0^t v(t) \sin(\theta(t)) dt \quad (9)$$

$$\theta(t) = \theta_o + \int_0^t w(t) dt \quad (10)$$

The speeds are given by equation (11); the constants correspond to a positive integer value:

$$\begin{bmatrix} v \\ w \end{bmatrix} = \begin{bmatrix} v_r \cos \theta_e + k_x x_e \\ w_r + K_y v_r y_e + K_\theta v_r \sin \theta_e \end{bmatrix} \quad (11)$$

To be required the control using the position of the vehicle an error have to be generate for the robot configuration, these error can be obtain through the subtraction of the real and desired value of the position, this can be expressed in the equation (12) [11], [12].

$$\begin{bmatrix} X_e \\ Y_e \\ \theta_e \end{bmatrix} = \begin{bmatrix} \cos \theta_d & \sin \theta_d & 0 \\ -\sin \theta_d & \cos \theta_d & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} X_r - X_d \\ Y_r - Y_d \\ W_r - W_d \end{bmatrix} \quad (12)$$

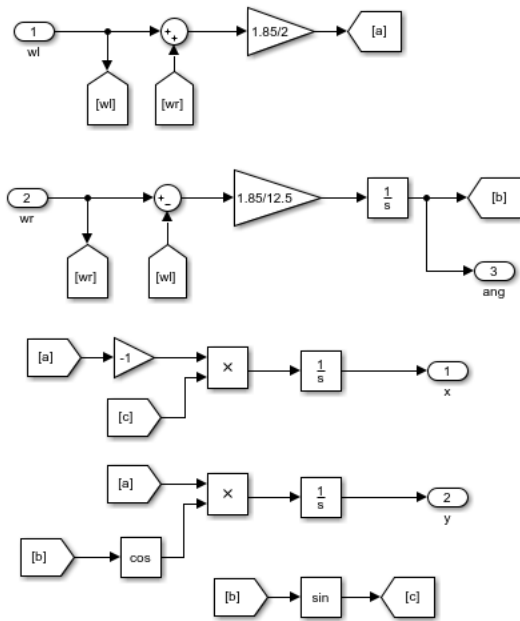


Figure 4. kinematics model differential robot.

Once obtained the speed for each wheels using the kinematics model, a PID control on the motors is required, this allow reducing the error. For the system characterization a generator-motor assembly was used, same as the one found in figure 6, using this configuration the transfer function was found (voltage vs. voltage), for obtain the final transfer function (velocity vs. voltage) the engine was characterized by speed. [13]

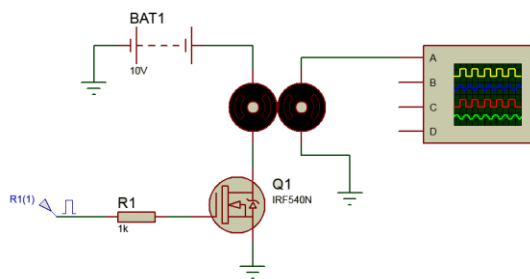


Figure 6. Assembly for the motor.

Using the montage on the figure 6, and using an oscilloscope, it can be seen results such as the ones found on the figure 7, which correspond to the signal input (square signal) and the output signal produce by the generator.

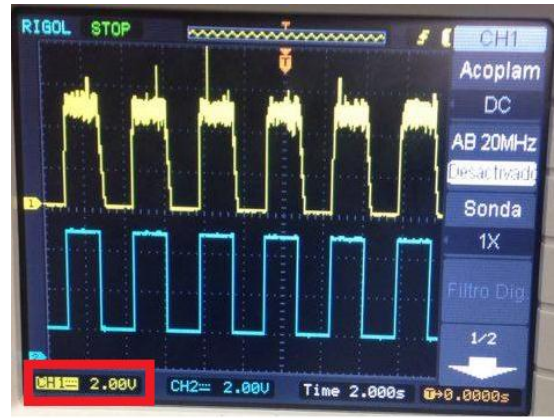


Figure 7. Input and output signals.

To calculate the transfer function of the system, a first order equation (13) was used and 92ms for the establishment time.

$$G(s) = \frac{k}{\tau s + 1} \quad (13)$$

The K constant can be found using the equation (14):

$$k = \frac{\text{output voltage}}{\text{input voltage}} \quad (14)$$

Knowing that the voltage generator is 5vpp, the k constant can be obtain from (14):

$$k = \frac{2}{5} = 0.4 \quad (14)$$

The equation (15) describes the establishment time in open loop:

$$T_{STA} = 5 * \tau \quad (15)$$

Knowing that the establishment time is 92ms, the tao value is obtained using the equation (15):

$$\frac{Y_{STA}}{5} = \tau = 0.0184 \quad (16)$$

The values previously obtained can be replace on the equation (13), this result in the transfer function, as seen in the equation (17) [14].

$$G(s) = \frac{0.4}{(0.0184)s + 1} \quad (17)$$

A PI control was implemented using the following parameters: 0.1 second as an establishment time and a zeta ( $\zeta$ ) equal to 0.7, obtaining the current values for the constants show in the

equation (18), the figure 8 verify the control using a step for the entrance signal.

$$PI = \frac{1.18s + 73.6}{s} \quad (18)$$

$$K_p = 1.18$$

$$K_i = 73.6$$

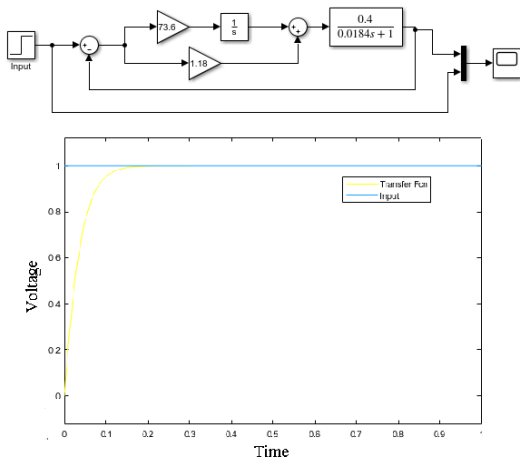


Figure 8. Control using a step.

The GPS device can obtain the current position for the vehicle; a SIM808 GPS was use on the project. This can be configured using the AT commands, using a microcontroller and the serial port. The GPS needs at least three satellites for a reading, can measure latitude, longitude and altitude [15], a kalman filter can be apply for better results [16].

Using the following command AT+CGPSINF=0 on the serial port, having the device connected, can be obtain a measure such as the one found on the figure 9, which corresponds to the following characteristics: mode, latitude, longitude, altitude, UTC horary, respond time, number of satellites, speed and course.

The encoders can be used to improve the position and speed measure for each wheel, besides, do not require a previous time, before start working unlike the GPS, also can be used as a support to increase the precision in the measurement of the vehicle [17].

```
OK
AT+CGPSINF=0
+CGPSINF: 0,443.576600,7403.331200,2574.600000,20180206223740.000,0,14,0.074080,115.510002
```

Figure 9. GPS data

### Neuronal network.

Using the cellphone application call IP Webcam the computer can obtain images from remote places, this app sent images to

an address so they can be processed using Python and the Framework Caffe. [18]

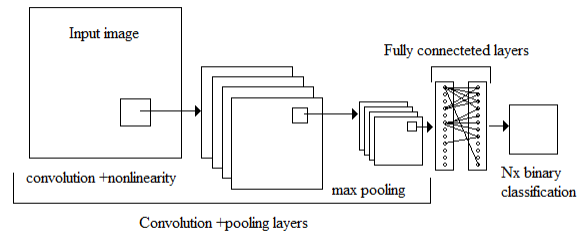


Figure 10. Neuronal network layers.

The figure 10 illustrate the function of a convolutional neuronal network, this is obtained through the input image and performs convolutions to obtain each of the results from the main image, it has 8 layers without the input one, when the image pass across a layer, a Blob is generate, this one is the input for the next layer, the Blob contain the required information for the process [19].

Caffe implements a method to perform optimization with minimum loss value, the objective minimize through the entire data set D, the solution method used is present on the equation (19).

$$L(W) = \frac{1}{|D|} \sum_i^{|D|} Fw(X^{(i)}) + \gamma r(W) \quad (19)$$

Where fw(x<sup>i</sup>) bellows to the loss information on the instant X<sup>i</sup> and r(w) is the gamma weigh regulation, using a stochastic approximation on the equation (19), the equation (20) can be obtain:

$$L(W) \approx \frac{1}{N} \sum_i^N Fw(X^{(i)}) + \gamma r(W) \quad (20)$$

Deep learning allow to extract information on al big information bank, this can be achieved by the number of neuronal and layers that has, by owning a huge amount of information it is possible to obtain a recognition of an object that is not totally visible with a high degree of fidelity [21].

### Sensors and reconstruction.

They were added five ultrasound sensors HC-SR04, for the identification of obstacles and the reconstruction in the work environment, the position of the sensors are show on the figure 11.

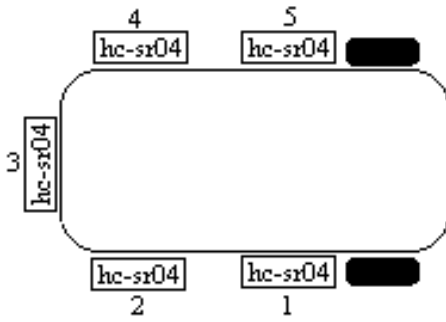


Figure 11. Hc-SR04 sensors

The sensors 2 and 4 have an inclination of 45 degrees, for the navigation of the mobil can be done using the sensors 1, 3 and 5. When one of the three elements mentioned above have a measurement range lower that 15 cm, generate a logic state depending on the value of these conditions the vehicle can produce an action, which is summarized in table 1.

Table 1. Sensor state

S1	S2	S3	State
0	0	0	Forward
0	0	1	Forward
0	1	0	Verify distance S1 and S3
0	1	1	Left
1	0	0	Forward
1	0	1	Forward
1	1	0	Right
1	1	1	180°

The ultrasound sensors, work sending a 10 microsecond's signal on High from a microcontroller to the Trigger pin, the sensor send eight pulses of 40 KHz and prepare the Echo pin until the microcontroller stop counting all the pulses. A counter is required to establish the time that the eight pulses delay in arriving. Once the operation is complete the Echo pin, reset his logic value to Low and the distance can be measure using the equation (21).

$$Distance = Speed * Time \quad (21)$$

Knowing that the signal have to make two travel before reached the sensor again, and the speed of sound is 340 m/s, the equation (21) shows the way to calculate the distance.

$$Distance_{cm} = time_{micro\ seconds} * 0.017 \quad (21)$$

Once the information of the sensor, current position of the vehicle and orientation are obtained, the data is send to a computer using a Bluetooth device. Using Python software and

the tools that gave OpenCV, a partial reconstruction of the environment is done. For the reconstruction it was used the geometric form of a line, the size of the vehicle is important for this operation without mentioning the current localization of the mobile. The procedure performed for this operation is presented in figure 12.

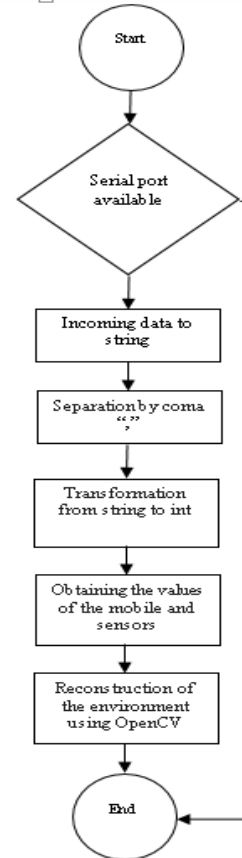


Figure 12. Data on Python

The interface for the manual control was made using the graphic library Tkinter, the application allow sending information through the communication port. [22]

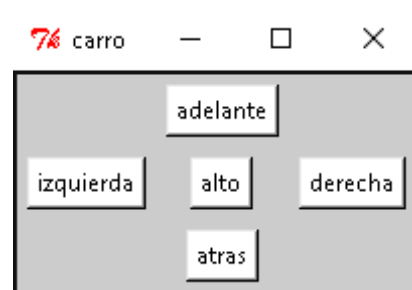
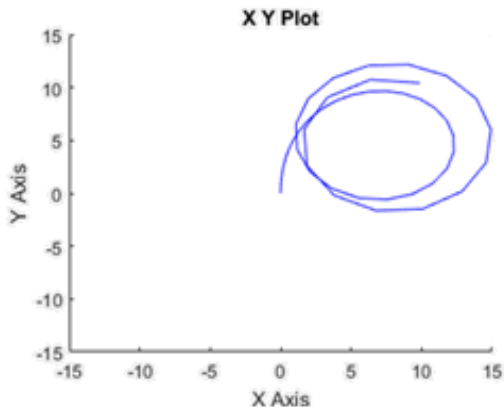


Figure 13. Manual interface

### ANALYSIS OF RESULTS

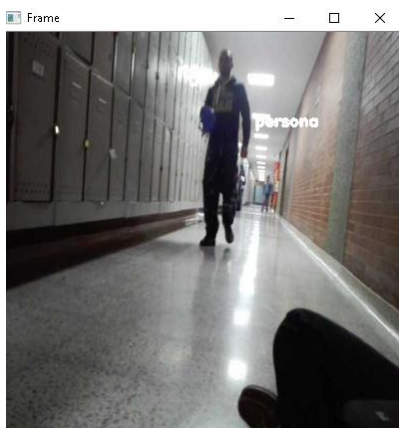
Then, it will going to show the results obtained on the implementation of the algorithm on the vehicle.

The kinematics model present on the figure 14 corresponds to a differential vehicle, as input parameters required the angular speeds for each wheel and the output will be the speed on the coordinate plane and the angular speed of the vehicle. For these test the input parameters were a ramp and sinusoidal signal for each wheel.



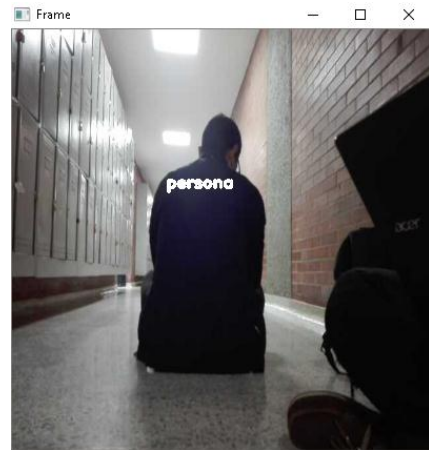
**Figure 14.** Kinematics model result

The corresponding measurements with GPS gave as a result an error lower from 2 meters, however, at the moment of using the devise on a scale excavator the resolution was lower than expected, this was in part by working on a small area (3 by 4 meters), the displacement of the vehicle was poorly measure, for this reason the encoders could work perfectly in this kind of applications.



**Figure 15.** Neuronal Network

Thanks to the use of a neural network the algorithm can identify different types of person on the same image, due that Deep Learning uses convolutional network allows the identification of more than one element involve on the image. The disadvantage of this kind of systems is the high information and the time that requires training this network, without mentioning the time of image processing to obtain the results. Due to this in some circumstances, it is better to use conventional Machine Learning methods, the results are show on the figure 15 and 16 [23].



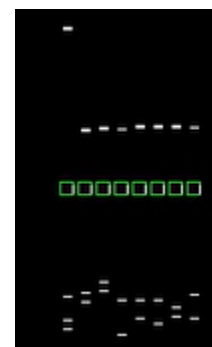
**Figure 56.** Neuronal Network

Likewise, the network can identify people who are sitting, half back, with a fidelity percentage higher that 90 percent.



**Figure 17.** Recognition without obstacles ultrasound

One of the principal problems of using ultrasound sensors is the signal processing in the same microcontroller, the measure of the sensor change depending on the quantity of objects present on the workspace, when the objects are near from the vehicle; the readings are more accurate as it show on figure 17.



**Figure 18.** vehicle with obstacles on the left

The figure 18 shows that in some cases, the reading in the sensor can produce two different values on the same point; these can be produce in part for the vehicle speed, the test were design for a linear movement, changing the obstacles near of the vehicle.



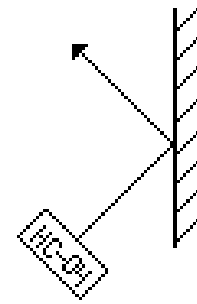
**Figure 19.** Recognition with obstacles

Having the sensor two and four whit a variation of 45 degrees, the picture 21, shows the deflection of the ultrasound sensors. There were some cases on the implementation when the measure was wrong, this is because the measured signal was redirected in another direction, for this reason the sensor mentioned above were discarded, the figure 19 and 20 illustrates the reconstruction in front of different types of obstacle.



**Figure 20.** vehicle with obstacles on the right

One of the principals problematic in the implementation of the vehicle was produce by the use of ultrasound sensor with a microcontroller, produce waiting the eight pulses required to recognize the distance of the object to be measured. Can produce data loss, rebound from other sensors and waste of time in the microcontroller, for this reason it is no recommended the use of these sensors for this kind of applications, or using FPGA devises for the increase in the processing speed of the generated information.



**Figure 21.** Errors produced by the sensor

As a future work it is planned the implementation of a visual odometry using ORB parameters, change the ultrasound sensors for laser sensors for obtaining a better resolution and the training of a neuronal network for the recognition of objects such as light poles, vehicles, among others.

## CONCLUSIONS

The implantation of a kinematics model that has input parameters the position of the vehicle and output the speed of each of the wheels of the mobile allows to have an absolute control of the position of the vehicle, allowing the movement of the excavator in a more precise way, the error margin is low (lower than 5 percent on the implementation), the error can be lowered using another kind of sensor, only if the system requires more precision.

Using a Deep Learning neuronal network the error produced by the over-training of the network can be reduce, additionally the number of patrons that the network can identify can be increased, with a fidelity percent higher than 90% the network can identify different elements without having wrong readings.

The use of multiple ultrasound sensor in the same microcontroller can generate problems such as noise incoming from other sensors and waste of time in processing signals, these can be observe on a low reconstruction of the environment, and even generate erroneous readings in the system, two different samples on the same position with different values, the error was reduce when the objects were near to the vehicle (error less than 10%) instead of having an error of 30% produce by the objects distance.

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