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Research Article

Parameter Estimation of Low-Cost Ultrasound and Laser Range Sensors to be Used for Mobile Robot Applications

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Abstract:

In this study parameters of sensor models are estimated for low-cost ultrasound and laser range sensors. Sensor models that are best suited to simultaneous localization and mapping (SLAM) tasks for mobile robotics applications are used. Mathematical functions of sensor models with relevant parameters to be determined are explained. Particle swarm optimization (PSO) algorithm is used to find the best parameters that explain the experimental measurements optimally. Experiments are conducted for various sizes of obstacles at various distances and results are reported detailly in the corresponding section. Finally, results are discussed and future works to be built on the results are proposed.

1. Introduction

Mobile robot applications mostly demand range finders for various tasks among which object avoidance, path planning and simultaneous localization and mapping (SLAM) are some important examples [1]. Autonomous robots and vehicles use sensors, cameras, and other technologies to make instant decisions without human supervision [2]. Significant progress has been made in recent years in autonomous vehicles in collision avoidance, determining optimal safe routes, detecting obstacles, identifying objects, and avoiding them. Yasin et al. (2021) developed an algorithm for shape estimation and collision avoidance for autonomous robots by rotating the sensor instead of moving around obstacles using a low-cost ultrasonic sensor. This approach has yielded satisfactory results in tests with different object shapes in indoor conditions [3]. Aliyu et al. (2017) developed a microcontroller-based collision avoidance system that performs safety braking when the minimum safety distance between the vehicle and the obstacle is reached. Automatic braking is performed by detecting obstacles and distances using ultrasonic sensors, and the response time of this system was measured as 0.86 seconds on average [4]. In a similar study, Derkach et al. (2020) proposed a real-time obstacle avoidance algorithm for a mobile robot equipped with a microcontroller and four ultrasonic sensors. The noise density was adjusted using the Kalman filter, and successful results were obtained with 4.15 s and 0.07 m RMSE [5]. Kai-Tai Song et al. (2004) de-signed an ultrasonic sensor system to prevent side collisions at low speeds and showed that the system was effective up to 40 km/h vehicle speed. This study also investigated the effects of wind on detection and found satisfactory results up to 35 km/h wind speed [6]. Jin et al. (2018) designed a rotation-controlled omnidirectional intelligent obstacle avoidance system instead of a fixed ultrasonic sensor to measure distance in smart cars. It was shown that the developed system can effectively improve autonomous obstacle avoidance's speed, precision, and obstacle avoidance rate [7].

Laser-based detection systems are also showing remarkable developments in this area. The time-of-flight laser receiver introduced by Ahola & Myllylä (1986) is used for object detection and distance measurement [8]. Zheng et al. (2021) developed laser-based human detection and obstacle avoidance algorithms for a robot that trans-ports materials along a reference path in a hospital environment [9]. Choon-Young Lee & Ju-Jang Lee (2000) proposed a hierarchical object recognition algorithm (HORA) for an adaptive cruise control system to filter out spurious detections and maintain the distance to the target vehicle. Also, with this algorithm, the movements of obstacles were detected, and their position changes were monitored [10]. Komarizadehasl et al. (2022) showed that the accuracy obtained by combining a set of similar sensors is higher than the prediction of a single sensor [11]. In addition, this study showed that a cheap analog distance sensor, HC-SR04, has higher prediction accuracy than expensive time-of-flight (ToF) sensors (VL53L0X and VL53L1X).

SLAM is comprised of building a map of environment while simultaneously positioning the mobile robot inside the built map [12]. Some early works on SLAM problem use ultrasound sensors [13, 14], while more recent works mostly use some kind of laser range sensors [15-17].

An important problem for mobile robots which involves SLAM as a part is active SLAM or A-SLAM for short. In A-SLAM, a mobile robot not only estimates surrounding map and its own position but at the same time controls its actions actively in order complete one or several tasks [18,19]. Most of recent works on A-SLAM utilize Lidar as main sensor [20-32].

For SLAM applications, a basic range measurement function with four types of measurement errors can be used to strongly represent sensor model: small inherent Gaussian measurement noise, errors due to unexpected objects which are closer than object of interest, errors due to complete failure to detect objects and random noise which cannot be explained deterministically [33].

In this study, mathematical functions of sensor models are explained and parameters are estimated for low-cost sensors for mobile robotics applications. A particle swarm optimization (PSO) algorithm is used to find the best parameters in experimental measurements at different distances.

2. Material and Methods

The STM32F407VG Discovery development kit, shown in Figure 1, was used to collect sensor data and transfer it to the computer. This kit includes a 168 MHz, 32-bit ARM-based STM32F407 microcontroller with floating-point unit (FPU) support. The development board features one mini-USB and one micro-USB port, which are used for programming, application communication, and debugging. The board has 4 USART (Universal Synchronous/Asynchronous Receiver Transmitters) and 2 UART (Universal Asynchronous Receiver Transmitters) units for serial communication.

In this study, the UART2 unit was used for serial communication, with PA2 and PA3 pins assigned as transmit (Tx) and receive (Rx) pins, respectively. The connection to the PC was established using a USB-RS232 converter.

Figure 1. *STM32f407VG Discovery kit.*

Serial communication was performed at 115200 bps baud rate, with 8-bit data length, one stop bit, and no parity bit. STM32CubeIDE program was used to program the Stm32F407 microcontroller. The program is available free of charge. I2S communication was used for laser sensor measurements. For the ultrasonic sensor, digital inputs and outputs were used with two timers.

2.1 Ultrasonic Range Sensors

Two type of range sensors used in mobile robotic applications: ultrasonic and laser. Ultrasonic range sensors are based on sound waves and measuring the time-of-flight passing in between transmission of sound wave and detection of reflected wave from object of interest. Laser range sensors work on a similar principle of time-of-flight measurement, but instead of sound, they use light in the form of a laser. Each sensor has its own advantages and disadvantages; however, laser sensors are generally more accurate but also more expensive.

Ultrasound range sensors transmit a modulated sound wave and listen for the reflection of the modulated signal. Once the reflected wave is received, the time elapsed between transmission and reception is used to calculate the distance of the object of interest. In this study, a popular low-cost ultrasound sensor, namely HC-SR04, is used which is shown in Figure 2. The sensor has four pins, VCC, GND, TRIG and ECHO, where GND is common ground, VCC is 5 Volts power supply input, TRIG is the digital input signal to the sensor to trigger it to transmit ultrasound wave and ECHO is the sensor output signal. ECHO signal's width is proportional to the distance measured so by measuring the width of this digital signal, distance measured is inferred by the computing circuitry of mobile robot. These four pins can be connected to either microprocessor-based computing circuitry or FPGA

Figure 2. *A popular low-cost ultrasound sensor: HC-SR04.*

These four pins can be connected to either microprocessor-based computing circuitry or FPGA based computing circuitry. When interfacing with computing circuitry, it is important to use digital logic converters of 5 Volts to 3.3 Volts if needed, otherwise computing circuitry may be harmed. Some of the specifications of the ultra-sound sensor are as follows:

- Power Supply: +5V DC
- Quiescent Current: <2mA
- Working current: 15mA
- Effectual Angle: <15º
- Ranging Distance: 2-400 cm
- Resolution: 0.3 cm
- Measuring Angle: 30º
- Trigger Input Pulse width: 10uS
- Dimension: 45mm x 20mm x 15mm
- Weight: approx. 10 g

2.2 Laser Range Sensors

Laser range sensors' working principle is similar to that of ultrasound range sensors but their performance is clearly superior. In this study, a low-cost laser range sensor, namely VL53L0X, is used which is shown in Figure 3.

Figure 3. *A low-cost laser sensor: VL53L0X.*

The sensor has four pins, two of which are ground and 5 Volts power supply. The other two pins are for I2C communication, namely SCL and SDA pins. SCL is for clock and SDA is for data. I2C address can be programmable for the onboard chip on the sensor but for the development card it is fixed to 0x29. Some specifications for the laser range sensor are as follows:

- Power Supply: +3-5V DC
- Working current: 40 mA
- Effectual Angle: <25º
- Ranging Distance: 3-200 cm
- Dimension: 20 mm x 11 mm
- Weight: approx. 1.5 g
- Working temperature: -20C - +70C
- Wavelength: 940 nm

3. Theory

The first part of the model is about measuring object of interest with small Gaussian noise. Mean of the Gaussian is at the true object location while the standard deviation depends on the precision of the sensor. The mathematical model of this part is represented as:

$$p_1(x,m) = \begin{cases} \rho N(z, z^*, \sigma_1^2)\ , & if\ 0 \leq z \leq z_{max} \\ 0 & , otherwise \end{cases} \quad (1)$$

where z is measured distance, z* is true distance and σ1 is variance of sensor noise. This part is generally most probable for explaining measured value.
The second part of the model is about missing object of interest and any other object in the field of view all together. This returns either maximum range of sensor or greater value and can be represented with the following equation:

$$p_2(x,m) = \begin{cases} 1 & , if\ z = z_{max} \\ 0 & , otherwise \end{cases} \quad (2)$$

Third part of the model is about random unexplainable measurements. This can be modelled using uniform distribution with the following equation:

$$p_3(x,m) = \begin{cases} \frac{1}{z_{max}} & , if\ 0 \leq z \leq z_{max} \\ 0 & , otherwise \end{cases} \quad (3)$$

Fourth and last part of the model is about measuring objects not existing in the map with measured distance nearer than object of interest and represented with the following equation:

$$p_4(x,m) = \begin{cases} \rho \alpha_{short} e^{-\alpha_{short} z} & , if\ 0 \leq z \leq z^* \\ 0 & , otherwise \end{cases} \quad (4)$$

where αshort is a parameter of the sensor.
These four equations are mixed by constant coefficients defined by the parameters z_1, z_2, z_3 and z_4 where $z_1 + z_2 + z_3 + z_4 = 1$ and final mathematical model of the sensor is given by the equation:

$$p(z,m) = z_1 * p_1(x,m) + z_2 * p_2(x,m) + z_3 * p_3(x,m) + z_4 * p_4(x,m) \qquad (5)$$

So, the mathematical model of the sensor is represented by an equation with 6 independent parameters namely σ_1, z_1, z_2, z_3, αshort and z_4. Any range sensor with the assumptions above can be represented with this mathematical model.
There are six parameters to be found for each sensor as explained in the section above. In order to fit the mathematical function representing the sensor models to experimental results, a popular iterative optimization algorithm, namely particle swarm optimization (PSO), is used since it proved its credibility in various optimization applications [34-40].
PSO is an iterative optimization algorithm inspired from movements of colonies of animals in nature [41]. It is utilized in various systems, including mobile robot systems [42]. Candidates of optimum parameter values are represented by particles in parameter space. Each particle has a position and velocity at each epoch of iteration represented by x_i and v_i, respectively. Position update of each particle is simple as shown in equation 6 below.

$$x_i[n] = x_i[n-1] + v_i[n] \qquad (6)$$

where n is the epoch number.

Velocity update of each particle is done using three sources of information:

- Particle's previous velocity;
- Particle's known optimum point upto that iteration;
- Swarm's known optimum point upto that iteration.

Each source of information is multiplied by a scalar number and added to obtain the new velocity of the particle as shown in Equation [7] below:

$$v_i[n] = c_1 v_i[n-1] + c_2 p_i[n-1] + c_3 g_i[n-1] \qquad (7)$$

where p_i is particle's known optimum point up to current iteration, g_i is swarm's known optimum point up to current iteration and c_1, c_2 and c_3 are scalar values specific to application.
In order to use the sensor measurements in PSO algorithm, a histogram is obtained for each real object distance. After the histogram is obtained, a fit score is calculated for each parameter point and input to the PSO algorithm in order to search for the optimum value.

4. Results and Discussions

Measurements were taken for 17 different distances, ranging from 2 cm to 150 cm. The TOF sensor is unable to make accurate measurements at distances exceeding 150 cm. Table 1 is ultrasonic sensor parameter. It is observed that both sensors are quite precise but ultrasound sensor has some short measurements for some distances. This can be due to the crosstalk between the ultrasonic transmitter and receiver, which is common in ultrasonic sensors. Table 2 is laser sensor parameter.

Table 1. *Ultrasonic Sensor Parameter*

(cm)	1.	2.	3.	4.	5.	6.
2	<0,001	1	0	0	0	0
5	<0,001	1	0	0	0	0
10	<0,001	1	0	0	0	0
20	<0,001	1	0	0	0	0
30	<0,001	1	0	0	0	0
40	<0,001	1	0	0	0	0
50	<0,001	0,99506098	0	0	0,00493902	0
60	<0,001	0,98499737	0	0	0,01500263	0
70	<0,001	0,97935834	0	0	0,02064166	0
80	<0,001	0,98039773	0	0	0,01960227	0
90	<0,001	0,97497832	0	0	0,02502168	0
100	<0,001	0,97415114	0	0	0,02584886	0
110	<0,001	0,96545862	0	0	0,03454138	0
120	<0,001	0,9649951	0	0	0,0350049	0
130	<0,001	0,9599992	0	0	0,0400008	0
140	<0,001	0,95521914	0	0	0,0447809	0
150	<0,001	0,95495903	0	0	0,04504097	0

Table 2. *Laser Sensor Parameter*

(cm)	1.	2.	3.	4.	5.	6.
2	<0,001	1	0	0	0	0
5	<0,001	1	0	0	0	0
10	<0,001	1	0	0	0	0
20	<0,001	1	0	0	0	0
30	<0,001	1	0	0	0	0
40	<0,001	1	0	0	0	0
50	<0,001	1	0	0	0	0
60	<0,001	1	0	0	0	0
70	<0,001	1	0	0	0	0
80	<0,001	1	0	0	0	0
90	<0,001	1	0	0	0	0
100	<0,001	1	0	0	0	0
110	<0,001	1	0	0	0	0
120	<0,001	1	0	0	0	0
130	<0,001	1	0	0	0	0
140	<0,001	1	0	0	0	0
150	<0,001	1	0	0	0	0

5. Conclusions

This study estimates the parameters of sensor models for low-cost ultrasonic and laser ranging sensors suitable for mobile robotics applications. The mathematical functions of sensor models with relevant parameters to be determined are explained. A particle swarm optimization (PSO) algorithm is used to find good parameters from experimental measurements. Experiments are conducted for obstacles of different sizes at various distances.

Note that experimental results show the precise nature of both ultrasonic and laser sensors but laser sensor is slightly more reliable. As future work these sensors are to be used in real mobile robotic experiments.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
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