# 3D Space Mapping Using Ultrasonic Sensor 

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#### Abstract

$\boldsymbol{A b s t r a c t}$ : This study has been undertaken which proposes a way to use the Ultrasonic sensor to map the space in 3D. In this project, an Ultrasonic sensor is used to map the area using Multivariate Gaussian Distribution. The Ultrasonic sensors give the reading for the distance of object. This reading is then used to calculate the probability of position of obstacle in the field of vision of that particular sensor. The Multivariate Probability Distribution function has two variables ' $r$ ' and ' $\theta$ ' (theta) which are varied at particular instants to find the probability at each cell.


## IndexTerms - Gaussian Probability Distribution Function, Ultrasonic sensors, Baye's Law, 3D mapping

## 1.InTRODUCTION

The fundamental property of an ultrasonic sensor is to measure the distance of the object in its field of vision. The operator certainly does not know the position, shape, size of the obstacle. The only information that can be achieved is the distance of the obstacle. Using the method given the paper one can map the surrounding using multiple ultrasonic sensors and approximate the nature of the surrounding. This method of mapping can be used to map surrounding in automotive for parking assistance, to map sea beds, and underwater landscape.

## 2. SYSTEM OVERVIEW

The project aims to map the surrounding so that the detection of space is possible. The mapping is done using ultrasonic sensors. Multiple sensors will be used to get the distance of an object. Using the distance, and the probabilistic function $\mathbf{F}(\mathbf{r}, \boldsymbol{\theta})$ we find the probability of occupancy of each cube in the field of vision of each sensor ${ }^{[1][2]}$. On the basis of this probability a color is allotted to the cube which will result in a depth map of the surrounding ${ }^{[6]}$.

All ultrasonic sensors have different beam widths and sensing range, even every ultrasonic sensor shows different behavior in different environments. We have considered a sensor having a beam of 30 cm in radius. Also the environment for our research is considered to be static.

In this research we have considered cylindrical coordinate system for calculating probability of cubes as the beam of a ultrasonic sensor is a cone and mapped as per cartesian coordinate of the corresponding cubes ${ }^{[4]}$.

## 3. Probabilistic Model For Ultrasonic sensor

Different sensor readings will be from an ultrasonic sensor array. As per the obstacle there will be different sensor readings. Each sensor reading will be used to calculate probability of the cubes under the field of vision of the corresponding sensor. These probabilities are used to allot a particular color to the cell. This will result in a depth map of the surrounding area.
Derivation for Probabilistic Distribution Function (P.D.F)
The generic form for multivariate P.D.F is given by;

$$
\mathrm{F}\left(x_{1}, x_{2}\right)=\frac{1}{(2 \pi)^{\frac{d}{2}}|\Sigma|^{\frac{1}{2}}} e^{\left\{\frac{-1}{2}\left[(X-\mu)^{T} \Sigma^{-1}[X-\mu]\right]\right\}}
$$

In our case we are using two variables which are independent of each other i.e. 'r' \& ' $\theta$ '
Therefore, $\mathrm{d}=2$
Mean matrix;

$$
\begin{equation*}
\mu=\left[\mu_{r} \mu_{\theta}\right] \tag{1}
\end{equation*}
$$

Covariance matrix;

$$
\Sigma=\left[\begin{array}{llll}
\sigma_{r}^{2} & 0 & 0 & \sigma_{\theta}^{2} \tag{2}
\end{array}\right]
$$

element $(1,2) \&(2,1)$ is zero because covariance between $r \& \theta$ is zero as both are independent variables. Now;

$$
\begin{equation*}
\mathrm{X}=(r \theta) \tag{3}
\end{equation*}
$$

from (1) \& (3)

$$
\begin{gather*}
\mathrm{X}-\mu=\left[r-\mu_{r} \theta-\mu_{\theta}\right] \ldots .  \tag{4}\\
{[X-\mu]^{T}=\left[r-\mu_{r} \theta-\mu_{0}\right] .} \tag{5}
\end{gather*}
$$

from (2);

$$
\begin{gathered}
|\Sigma|=\left(\sigma_{r}^{2} \cdot \sigma_{\theta}^{2}\right)-0=\sigma_{r}^{2} \cdot \sigma_{\theta}^{2} \\
\Sigma^{-1}=\frac{1}{|\Sigma|} \operatorname{adj}(\Sigma) \\
\operatorname{adj}(\Sigma)=\left[a_{11} a_{12} a_{21} a_{22}\right]=\left[\begin{array}{lll}
\sigma_{r}^{2} & 0 & 0 \\
\sigma_{\theta}^{2}
\end{array}\right] \\
a_{i j}=(-1)^{i+j}\left|a_{i j}\right| \\
a_{11}=(-1)^{1+1}\left|a_{11}\right|=(-1)^{2} \cdot \sigma_{r}^{2}=\sigma_{r}^{2}
\end{gathered}
$$

$$
\begin{gather*}
a_{12}=(-1)^{1+2}\left|a_{12}\right|=(-1)^{3} \cdot 0=0 \\
a_{21}=(-1)^{1+2}\left|a_{21}\right|=(-1)^{3} \cdot 0=0 \\
a_{22}=(-1)^{2+2}\left|a_{22}\right|=(-1)^{2} \sigma_{\theta}^{2}=\sigma_{\theta}^{2} \\
\Sigma^{-1}=\frac{1}{\sigma_{r}^{2} \cdot \sigma_{\theta}^{2}}\left[\begin{array}{llll}
\sigma_{r}^{2} & 0 & 0 & \sigma_{\theta}^{2}
\end{array}\right]=\left[\begin{array}{llll}
\frac{1}{\sigma_{r}^{2}} & 0 & 0 & \frac{1}{\sigma_{\theta}^{2}}
\end{array}\right] \\
\left.\Sigma^{-1}=\left[\begin{array}{llll}
\frac{1}{\sigma_{r}^{2}} & 0 & 0 & \left.\frac{1}{\sigma_{\theta}^{2}}\right] \ldots \ldots \ldots .
\end{array}\right] . .6\right) \tag{6}
\end{gather*}
$$

Now, from (4), (5) \& (6);

$$
\begin{align*}
&(X-\mu)^{T} \Sigma^{-1}(\mathrm{X}-\mu)=\left[\begin{array}{ll}
r-\mu_{r} & \theta-\mu_{\theta}
\end{array}\right] \cdot\left[\begin{array}{lll}
\frac{1}{\sigma_{r}^{2}} & 0 & 0 \\
\left.\frac{1}{\sigma_{\theta}^{2}}\right] \cdot\left[r-\mu_{r}\right. & \theta-\mu_{\theta}
\end{array}\right] \\
&=\left[\frac{r-\mu_{r}}{\sigma_{r}^{2}}+0 \quad 0+\frac{\theta-\mu_{\theta}}{\sigma_{\theta}^{2}}\right]\left[r-\mu_{r} \theta-\mu_{\theta}\right] \\
&(X-\mu)^{T} \Sigma^{-1}(\mathrm{X}-\mu)=\frac{\left(r-\mu_{r}\right)^{2}}{\sigma_{r}^{2}}+\frac{\left(\theta-\mu_{\theta}\right)^{2}}{\sigma_{\theta}^{2}} \ldots \ldots \ldots(7) \tag{7}
\end{align*}
$$

So;


Hence;

$$
\begin{equation*}
\mathrm{F}(\mathrm{r}, \theta)=\frac{1}{(2 \pi) \cdot\left(\sigma_{r} \cdot \sigma_{\theta}\right)} e^{\left\{\frac{-1}{2}\left[\frac{\left(r-\mu_{r}\right)^{2}}{\sigma_{r}^{2}}+\frac{\left(\theta-\mu_{\theta}\right)^{2}}{\sigma_{\theta}^{2}}\right]\right\}} \tag{8}
\end{equation*}
$$

## 4. Methodology

### 4.1 Probability of single cube

Consider the sensor cone to be a cone. The cone is divided into number of small cubes of same dimensions. The multivariate P.D.F consist of ' $r$ ' and ' $\theta$ '[4] , the $r$ is the length of the vector joining the center of a particular cube to sensor position (i.e. $r 1$ in Fig.4.1) and $\theta$ (theta) is the angle made by the vector joining the particular cube center and the center axis (i.e. $\theta 1$ in Fig.4.1) ${ }^{[3]}$.


Fig.4.1 Sensor Wave
Using trigonometry one can find ' $r$ ' and ' $\theta$ ' for a particular cube. ' $\mu \mathrm{r}$ ' and ' $\mu \theta$ ' are the mean values for r and $\theta$. $\mu \mathrm{r}$ will be the reading given by the ultrasonic sensor, it will be fixed for all r and $\theta$ values. $\mu \theta$ is the angle where the probability of object is maximum i.e. the center axis and $\theta$ will be zero at the center axis.

Variance i.e. ' $\sigma r^{2}$ ' and ' $\sigma \theta^{2}$ ' can be calculated by the formula given below;

$$
\sigma_{r}^{2}=\frac{\sum_{i=0}^{n}\left(r_{i}-\mu_{r}\right)^{2}}{n} \text { and } \sigma_{\theta}^{2}=\frac{\sum_{i=0}^{n}\left(\theta_{i}-\mu_{\theta}\right)^{2}}{n}
$$

Here,
$\sigma_{r}^{2} \& \sigma_{\theta}^{2}$ are the variance for r and $\theta$
$\mu_{r} \& \mu_{\theta}$ are the mean values for r and $\theta,\left(\mu_{\theta}=0\right)$
n is the number of cubes
The standard deviation in the square root of the variance i.e. $\sigma r$ and $\sigma \theta$.
By substituting these values is the Multivariate Probability Distribution Function (8) one will get the probability of a particular cube.

### 4.2 Merging values from two or more sensors

When one uses two or more sensors for plotting. The sensor beam should coincide with each other. The value of the probability of the individual sensor is not sufficient for accurate mapping. So, we use Baye's filter, Baye's filter considers the Probability of the current reading, Probability of reading till previous reading \& the probability set at the start of the scanning and finding their odds to calculate odds of the cell at particular reading \& timestamp and convert odds to Probability.
Baye's Law states that;

$$
P(y)=\frac{P(x) \cdot P(x)}{P(y)}
$$

To find Odds;

$$
\text { Odds }=\frac{\text { Probability of something happening }}{\text { Probability of something not happening }}
$$

$$
O d d s=\frac{P(x)}{1-P(x)}=\frac{P(x)}{P(x)}
$$

Estimation of Map;

$$
\frac{P\left(m_{i} \mid z_{1: t}\right)}{1-P\left(m_{i} \mid z_{1: t}\right)}=\frac{P\left(m_{i} \mid z_{t}\right)}{1-P\left(m_{i} \mid z_{t}\right)} \times \frac{P\left(m_{i} \mid z_{1: t-1}\right)}{1-P\left(m_{i} \mid z_{1: t-1}\right)} \times \frac{1-P\left(m_{i}\right)}{P\left(m_{i}\right)}
$$

## Here;

LHS is the odds
In the RHS $1^{\text {st }}$ term is the current reading odds, $2^{\text {nd }}$ term is the odds of reading latest point, $3^{\text {rd }}$ term is Prior odds (starting value) Let,

Therefore,

$$
P\left(z_{1: t}\right)=P(x)
$$

$$
\therefore P(x)=\frac{1}{o d d s(x)=\frac{P(x)}{1+P(x)}} \begin{gathered}
\operatorname{odds}(x) \\
1+\frac{1}{o d d s(x)}
\end{gathered}=\frac{\operatorname{odds}(x)+1}{o d d s(x)}
$$

## 5. Simulation and Analysis



Fig.5.1 Simulation scenario
Assuming the scenario in Fig5.1 where sensor S1 gives the reading as 100 cm and sensor S 2 gives the reading as 50 cm . After recording these readings and applying to the algorithm and simulating the map on excel we get. We also assume that the field of vision of the sensor is divided into a number of cubes of dimensions $3 \mathrm{~cm} \times 3 \mathrm{~cm} \times 3 \mathrm{~cm}$.

| Sensor reading | 100 | $\mu \theta$ | 0 |  | $\mu \mathrm{r} 1$ | 100 |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| resolution | 3 |  |  |  |  |  |  |
|  |  |  | $\theta$ |  |  |  |  |
| cube distance | cube no. |  | degrees | $(\theta-\mu \theta)^{\wedge} 2$ | $\mathrm{r}_{\mathrm{n}}$ | $(\mathrm{r}-\mu \mathrm{r})^{\wedge} 2$ | $\mathrm{f}(\mathrm{r}, \theta)$ |
| 0 | 0 |  | 0 | 0 | 100 | 0 | 0.007514305 |
| 3 | 1 |  | 1.718358002 | 2.952754222 | 100.0449899 | 0.002024089 | 0.007402005 |
| 6 | 2 |  | 3.433630362 | 11.78981747 | 100.1798383 | 0.032341811 | 0.007056823 |
| 9 | 3 |  | 5.142764558 | 26.4480273 | 100.4041832 | 0.163364043 | 0.006461263 |
| 12 | 4 |  | 6.842773413 | 46.82354798 | 100.7174265 | 0.514700777 | 0.005609677 |
| 15 | 5 |  | 8.53076561 | 72.77396189 | 101.1187421 | 1.251583843 | 0.00453754 |
| 18 | 6 |  | 10.20397372 | 104.1210797 | 101.6070864 | 2.582726591 | 0.003344247 |
| 21 | 7 |  | 11.85977912 | 140.6543608 | 102.1812116 | 4.757683958 | 0.002186793 |
| 24 | 8 |  | 13.49573328 | 182.1348168 | 102.8396811 | 8.063788508 | 0.001230343 |
| 27 | 9 |  | 15.10957512 | 228.2992604 | 103.5808863 | 12.82274646 | 0.000575478 |
| 30 | 10 |  | 16.69924423 | 278.864758 | 104.4030651 | 19.38698218 | 0.000215503 |
|  |  |  |  |  |  |  |  |
|  |  |  | sum | 1094.862385 | sum | 49.57794226 |  |
|  |  |  | divide | 99.53294405 | divide | 4.50708566 |  |
|  |  |  | $\sigma \theta$ | 9.976619871 | $\sigma r$ | 2.122989793 |  |

Table 5.1 Function values for sensor S1
Table 5.1 shows the r and $\theta$ values for different cubes over a half beam width. The probability values when plotted form a Half Gaussian curve for half beam width as shown in Fig.5.1.


Fig. 5.1 Half Gaussian Probability Distribution Function
In Figure 5.1, the X axis shows the cube distance from the sensor position and the Y axis shows the function value of the corresponding cubes. As we move away from the sensor position the probability of a cell being empty decreases and eventually will tend to zero. Similar plot was plotted for a sensor giving a value of 50 cm (Fig5.2).

| sensor reading | 50 | $\mu \theta$ | 0 |  | $\mu \mathrm{r} 2$ | 50 |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  | $\theta$ |  |  |  |  |
| cube distance | cube no. |  | degrees | $(\theta-\mu \theta)^{\wedge} 2$ | r2 | $(\mathrm{r}-\mu \mathrm{r})^{\wedge} 2$ | $\mathrm{f}(\mathrm{r}, \theta)$ |
| 0 | 0 |  | 0 | 0 | 50 | 0 | 0.002069765 |
| 3 | 1 |  | 3.433630362 | 11.78981747 | 50.08991915 | 0.008085453 | 0.002035613 |
| 6 | 2 |  | 6.842773413 | 46.82354798 | 50.35871325 | 0.128675194 | 0.001931738 |
| 9 | 3 |  | 10.20397372 | 104.1210797 | 50.80354318 | 0.645681648 | 0.001755991 |
| 12 | 4 |  | 13.49573328 | 182.1348168 | 51.41984053 | 2.015947127 | 0.001511188 |
| 15 | 5 |  | 16.69924423 | 278.864758 | 52.20153254 | 4.846745545 | 0.001212061 |
| 18 | 6 |  | 19.79887635 | 391.9955049 | 53.14132102 | 9.867897765 | 0.000888996 |
| 21 | 7 |  | 22.78240573 | 519.0380109 | 54.23098745 | 17.90125482 | 0.00058357 |
| 24 | 8 |  | 25.64100582 | 657.4611797 | 55.4616985 | 29.83015046 | 0.00033494 |
| 27 | 9 |  | 28.36904629 | 804.8027876 | 56.82429058 | 46.57094193 | 0.000164024 |
| 30 | 10 |  | 30.96375653 | 958.7542186 | 58.30951895 | 69.04810515 | $6.68491 \mathrm{E}-05$ |
|  |  |  |  |  |  |  |  |
|  |  |  | sum | 3955.785722 | sum | 180.8634851 |  |
|  |  |  | divide | 359.6168838 | divide | 16.44213501 |  |
|  |  |  | $\sigma \theta$ | 18.96356727 | or | 4.054890258 |  |

Table 5.1 Function values for sensor S2
Table 5.1 shows the r and $\theta$ values for different cubes over a half beam width. The probability values when plotted form a half Gaussian curve for half beam width as shown in Fig.5.2.


Fig. 5.2 Half Gaussian Probability Distribution Function
As ultrasonic sensors are symmetric around the axis of the wave, after finding probabilities in one plane we can rotate those probability around the axis of the wave and a 3D probability map can be plotted. An Excel simulation is shown Table 5.3 of sensor which gives the reading of 100 cm .

|  |  | equi-dimensional cute numbers |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | \$100 | 20 | 9 | 8 | 7 | 6 | 5 | 4 | 3 | 2 | 1 | 0 | 1 | 3 | 3 | 4 | 5 | 6 | 2 | 13 | 9 | 110 |
|  | 10 | p0002 | 0,0noz | מ.nooz | 0.00072 | 0.0002 | 0.00022 | 0.0008 | 0,00022 | a.tone | 0,00012 | 0.00022 | 0000012 | 0.0008 | 0,00022 | 0.0072 | 0 0ranz | 000022 | 0.0007 | 0.0002 | 0.0008 | asood |
|  | 0 | 0.0002 | 0.0006 | 0.0006 | 0.0025a | 0.000ti | 0.00058 | 0.0006 | 120005 | 0.0006 | 0.000sa | 0.00058 | 00006s | -.c006 | [1000) 018 | -0.00sa | 0.00056 | 0.00098 | 0.00006 | [10000t | 0.0006 | docen |
|  | 8 | 0.0002 | 0,0000 | 0.0012 | 000123 | 0.0012 | 0.00123 | 0.0012 | 0,00123 | 0.0012 | 0.00122 | 0.00123 | 0,00123 | 0.0012 | 0.00123 | 000123 | 0.00123 | 0.00123 | 0.0012 | 0.0012 | 0.0000 | a0002 |
|  | 7 | $0 \mathrm{0cog}$ | 0,0niab | 0.0017 | 0.001219 | 12.0022 | 0.0.0219 | 6.902 | 4,00219 | H.D023 | 000719 | gucals | a00111 | p.0012 | If n0211 | tuou15 | 4.00219 | a00013 | 0.0022 | 0,0012 | 00006 | 0.000\% |
|  | 6 | 0009\% | 0.0006 | 0.0012 | 0.00219 | 0.0033 | 0.00144 | 0.0013 | 0,00334 | 0.0033 | Q00374 | Q,003)4 | 0.0014 | 0.0011 | 0.00334 | Q,00334 | $0.003) 4$ | 0.00334 | 0.0022 | 0.0012 | 00006 | (000\% |
|  | 5 | 0.0002 | 0.0006 | 0.0012 | 0.00219 | 0.0033 | 0.00534 | 0.004s | 0.00454 | 0.0045 | a.00454 | 0.00434 | 0.00454 | 0.0045 | 0.00454 | 0.00454 | 0.00454 | 0.00334 | 0.0027 | 0,0012 | 0.0000 | 60002 |
|  | 4 | 0.0038 | 8.0005 | a.na12 | 0.00219 | E.co33 | 0.00454 | ditas | 10.00561 | 11.0058 | a, 0 ¢5nt | d.001561 | 0.00561 | 10.056 | 1ai8561 | B00561 | 0.00454 | 0.00314 | 0.0422 | (0.0012 | Q0006 | 20002 |
| $\mathrm{m}^{\text {a }}$ | 3 | 0000 | 0,0006 | 0.0012 | (0002t9 | 0.0033 | 0.00854 | 00056 | 900090 | 0.0065 | 0.00046 | Q00066 | 000046 | 0.006 | y, 00605 | 900s61 | 0.00454 | 0.00134 | 0.0022 | W.0012 | 0.0006 | 6,000 |
| $e^{u}$ | 2 | 0.0002 | A.00006 | 0.0012 | 4.00219 | 4.8033 | 0.00454 | o olase | 80.0064a | u.har1 | 0.00756 | 0,00706 | D,00706 | 0.0071 | 0.0064 E | 1200561 | 0.00454 | 0.00334 | 0.0022 | 0.0012 | 0.0006 | <0002 |
| $e_{m}^{\mathrm{e}} \mathrm{~m}$ | 1 | 0.008 | a.0006 | 0.0012 | 0.001219 | 0.0033 | 0.30454 | 0.005 ${ }^{2}$ | 0.00646 | 0.0071 | 0.0024 | 0.0074 | 0.0074 | 0.807 | 1.00645 | 0.90561 | 0.00454 | 0.00114 | 8.6022 | 0.0012 | 0.006 | 0,0002 |
| $i b$ | 0 | 0.0002 | ti.0000 | 0.00112 | 0001219 | 8.0033 | 0.00454 | a.095 | 0,006al | 0.0071 | 00074 | 0.00751 | Q.0074 | 0.007 | 0.00646 | 0.0561 | 0.00956 | 0.00134 | 0.0072 | 7.0012 | 0.0000 | ם0000 |
| - | 1 | 0.0002 | 2.0006 | 0.0012 | 0.00219 | 0.0033 | 0.00454 | a-¢̆6 | Q 0064a | 0.0071 | 0.0074 | B. 01774 | 0.003A | Q.0071 | 800644 | 0 00s61 | 0.00454 | 2.00134 | 40022 | 0.0012 | 0.0066 | 2000 |
| ${ }_{\square}^{\circ}$; | 2 | 0.0002 | 0,0006 | d.0012 | 0.00219 | 0.0033 | 0.00454 | $0.005{ }^{\circ}$ | 0.00646 | $0.00 \times 1$ | 0.0076 | 0.0.0706 | 00076 | 0.007 | 0.00646 | Ecose 1 | 0.00454 | 0.00334 | 0,0022 | 0,0012 | a0000 | a0002 |
| $a^{3}$ | 3 | 0.0000 | 0.000it | 0.0012 | .0.01219 | 0.0033 | 0.00454 | danas | 4000646 | \%.now | 0.00646 | 0.006916 | व00646 | 2006s | 8.00646 | \#10¢ñ! | 0.0.3as ${ }^{\text {a }}$ | 0.00134 | 0.0027 | 0,0012 | 0.0006 | arocou. |
|  | 4 | 0.0001 | 6,0006 | 0.0012 | 0.00219 | 0.0033 | 0.00454 | 00056 | 0.00561 | 0.0056 | 0.00561 | Q,00561 | a, | 20006 | 0.00561 | -0,00561 | 0.00454 | 0.00334 | 0.0022 | $0.001 ?$ | 0,0006 | a0002 |
| 1 | 5 | 00002 | 0.0006 | 0.nu12 | 0.00219 | 0.0033 | 0.00534 | 0.0045 | 0.00454 | 0.0005 | 0.00454 | 0.00434 | 0.00454 | Q0015 | $0.0065 t^{2}$ | 0.00454 | 0,00954 | 0.00334 | 0.0022 | 0.0012 | 0.0066 | Q0000 |
|  | 6 | 0.0009 | 0.0006 | 0.0012 | 0.00219 | 2.0033 | 0.00334 | 4.0033 | f.00334 | 0.0033 | 0.00314 | Q,00334 | 0.00384 | 80.033 | +2.00334 | 0.00334 | 0.00334 | 0.60314 | 0.0023 | (t.0.12 | 0.0006 | Q0002 |
|  | 7 | 0.0000 | 0,0006 | 0.0012 | (100219 | 0.0022 | 0.0012 | 0,0072 | U00219 | 4.0072 | 0.0017 | 0,00219 | 000014 | 0.0022 | 000719 | 0.00019 | 0,00219 | 0.00914 | 0.0027 | 0.0012 | 00000 | \$6000 |
|  | B | 0.0002 | 4.0006 | 0,0012 | 0.00123 | [1.0012 | 0:00123 | 0.0012 | 10.00123 | 0.0012 | 0.00123 | 0.00123 | Q00123 | .0.0012 | 0.00123 | 0.00123 | 0,00123 | 0.00123 | 0.6012 | 0.0012 | 0,0006 | \%0000 |
|  | $9$ | $0.0000$ | 0.0006 | 0.0005 | a00058 | 0.0006 | 0.00058 | 0.0006 | d.0005 | 0.0005 | 0.00058 | 0.60058 | 0.0005 | 00606 | $0.0005 i 1$ | 0.90058 | 0.00058 | 0.00058 | 0.0006 | 0.0006 | 0.0006 | 0,000 |
|  | 10 | 000002 | D,0002 | 0.0002 | a100023 | 0.0002 | 0.00027 | 0.0007 | 8,00022 | 4.00as | 0,00002 | 0.00022 | 0,00072 | 0.0000 | 0,00022 | 0,0002 | 0.00022 | 0.00022 | 0.0002. | 0.0002 | Q0008 | 10020 |

Table 5.3 Mesh of probability distribution function
Table 5.3 shows the mesh of the probability distribution function values. The center cell is the cell right in front of the sensor and has the greatest function value (probability) than other cubes. The number in the first row and First column are the cube numbers in the X and Y axes, zero means the center position and the number goes on increasing in both the direction as we move away from the center. The P.D.F values are in the form of mesh, equal values are in the same color rings. Plotting a graph on the bases of this mesh we get a 3D probability Distribution Graph as shown in Fig.5.3;

3D Probabilistic model


Fig.5.3 3D probabilistic plot for sensor S1
In figure 5.3 X and Y axes show the cube positions as in Table 5.3 (row $1 \&$ column 1 ) and Z axis show the function values of corresponding cubes. Figure5.3 shows Probability Distribution of XY plane at a distance Z (sensor reading) from the sensor.
Similarly, we can plot a 3D probabilistic plot for sensor 2 (S2) refer figure 5.1 . which gives a reading of 50 cm .


Fig.5.4 3D probabilistic plot for sensor S2

When the two plots are equally scaled on the same plot. We get the following plot. (Figure 5.5)
Comparing readings


Fig.5.5 Comparing sensor plots
From Fig. 5.5 we can conclude that the function value for sensor S 1 giving a reading of 100 cm is larger than the function value for the sensor S 2 which gives a reading of 50 cm . Hence here it is proved that the probability od having a empty space is greater where sensor reading is greater.

## 6. CONCLUSION

From this research we conclude that, the derived, Multivariate Gaussian Probability Distribution function gives a function value to a particular cube in space on the basis of the cubes position with respect to the position of the ultrasonic sensor. Further the cube from the sensor, greater the function value of the corresponding cube.

## 7.ACKNOWLEDGMENT

This method of 3D mapping using ultrasonic sensor helps to scan the volume using Gaussian Probabilistic Distribution Function. This method can be used in space scanning in robots, in parking assistance for vehicles. As ultrasonics is used, one can also scan surface in other mediums like under water to scan sea beds and river beds.

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