Chapter 4

Indoor Beacon based Localization of Robots

4.1 Introduction

The ability of a robot to localize or identify its position in the field of deployment has the potential to transform several application domains including warehouse transportation, healthcare, greenhouse monitoring, etc. as indicated in Section 1.3. Greater flexibility in the movement of robots, higher cooperative behaviours and hence higher utilization of robots can be achieved if the robots can determine their position in the field of deployment. Moreover, any data collected over a distributed network has relavance only when associated with a timestamp and a location stamp. As presented in Section 2.2, most of the robotic networks are required to achieve only relative localization. Relative localization is the process of determination of the location of an object in two-dimensional (x, y) or three-dimensional (x, y, z) space with respect to a reference point (x_r, y_r, z_r) in the field of deployment [58]. In Chapter 3 of this thesis, a novel time synchronization scheme for SRS and MRS utilizing a wireless network was presented. In this chapter, the problem of two-dimensional relative localization of robots in indoor environments, which utilize a wireless network for communication is presented.

Localization is carried out in a robotic network in two phases-

1. Beacon based localization
2. Self-localization

In this chapter, the terms 'robots' and 'nodes' are interchangeably used. In the context of localization, the nodes which have known locations are generally referred to as reference or beacon nodes and the nodes which are to be localized are called as target nodes. Self-localization of a robot is described as the process of determination of its own position, using the information available with the robot or the information collected from its onboard sensors, without utilizing the information from the reference nodes. However, self-localization techniques are prone to accumulative errors, necessitating beacon based localization at regular intervals of time, thereby enabling the robots to correct their position.

In beacon based localization, the localization of target nodes is performed with the help of reference or beacon nodes available in the field of deployment. Different types of signals such as Ultrasound, Infrared, Wi-Fi, UWB as mentioned in Section 2.2.4 can be utilized as beacon signals. However, as discussed in Section 2.2.4, ultrasonic beacon based localization systems are cost-effective when compared to UWB systems and can provide better accuracy when compared to Wi-Fi and Infrared based systems. UWB signals may also be a source of interference for other systems, as UWB signals occupy a wide frequency spectrum (3.1-10.6 GHz) which is also assigned to technologies such as Wireless LAN (IEEE 802.11), radar and cellular systems [56]. In this chapter, ultrasonic signals are utilized as beacon signals for cost-effective localization of robots.

In indoor environments, the beacon signals are prone to Non-Line-of-Sight (NLOS) conditions due to the presence of obstacles and other moving objects. NLOS is generally described as the "large and always a positive error that arises when the distance between the transmitter and receiver is estimated from the measurement of signal transmitted between the transmitter and the receiver" [56]. The beacon signals may also get reflected and scattered leading to multipath effects. It is therefore critical to understand the impact of NLOS conditions on the beacon signal and to develop techniques that mitigate their effects. Indoor Localization Systems (ILS) which utilize ultrasonic beacons provide an accuracy in the order of approximately 1 to 2.5 meters under NLOS conditions while utilizing 3 to 8 beacons as described in Table 2.3. In the last few years, several machine learning techniques were utilized by researchers to characterize the effect of NLOS conditions on beacon signals using offline training process, followed by the identification and removal of

NLOS affected measurements during the localization process. However, it is time consuming and extremely cumbersome to obtain a comprehensive data set which represents the possible NLOS conditions in indoor environments.

In robotic systems, for ensuring their quick deployment, it is essential that the localization scheme incurs minimal offline calibration. To improve the wireless channel bandwidth utilization and to reduce the hardware cost, it is also necessary to reduce the number of beacon nodes in the system. In this chapter, an ultrasonic, beacon based, two-dimensional, indoor localization system using Time of Arrival (ToA) technique, wireless network and an artificial neural network is presented. In this chapter, the terms 'ToA' and 'ToF' are used interchangeably to represent the time taken by the ultrasonic signal to travel from the transmitter to the receiver. Similarly, the terms location and position are used interchangeably in this chapter. In this work, by utilizing ultrasonic beacons and wireless network, the ToA measurements are obtained accurately. An Artifical neural network (ANN) based location estimation scheme is proposed to estimate the location of the target node from the ToA measurements under Line-of-Sight (LOS) and NLOS conditions. One of the unique features of the proposed location estimation scheme is that the offline calibration of the system is required to be performed only under the LOS conditions. The accuracy in the recording of time of flight measurements is tested in hardware and the suitability of Artifical Neural Network (ANN) based location estimation scheme is validated through simulation of the proposed artifical neural network architecture.

4.2 Overall Architecture of Beacon Based Localization System

An ultrasonic beacon based indoor localization system is presented in this section. The proposed beacon based indoor localization system consists of three units or modules as shown in Figure 4.1. The units are Ultrasonic Unit, Central Unit and Location Estimation Unit. A detailed description of each of the units is provided in this section.

Ultrasonic Unit:

An ultrasonic receiver and transmitter circuitry for transmission and reception of ultrasonic beacons was designed and tested. Ultrasonic signals have a frequency range beyond the human hearing range, usually greater than 20 kHz. In an SRS or MRS system, if each robot requests the beacon or reference node for localization, then the network can become increasingly flooded with wireless

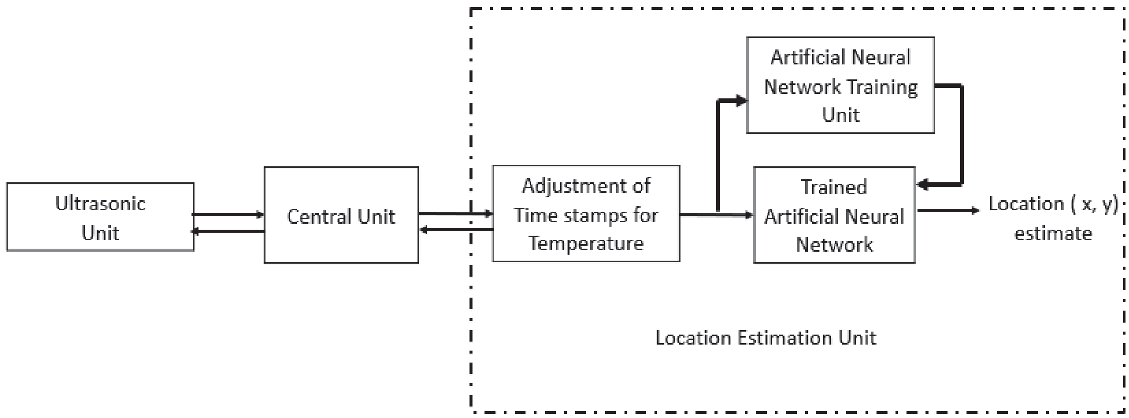


Figure 4.1. Overall architecture of the beacon based localization system.

messages requesting for localization. The proposed system is designed in such a way that the localization is initiated by the beacon nodes at periodic intervals of time. Hence, the ultrasonic unit of a target node was designed with only the ultrasonic receiver and the corresponding unit of the beacon node includes only ultrasonic transmitter. However, the choice of using both transmitter and receiver or utilizing only either of them on a robot can be made on the basis of the application, its requirements and constraints.

An important factor which affects the performance of ultrasonic transmitter/receiver is the choice of the ultrasonic transducer. The important factors that are to be considered while selecting an ultrasonic transducer are the frequency of operation, bandwidth and the beamwidth of the transducer. Commercially available ultrasonic transducers typically operate at frequencies between 40 kHz - 250 kHz. The attenuation of sound in air increases with the frequency as indicated in Figure 4.2 and as described by equation given below

$$\alpha(f) = 0.022 * f - 0.6 \tag{4.1}$$

where '$\alpha(f)$' is the attenuation of sound in dB/ft and 'f' is the frequency of sound in kHz [92]. Hence, ultrasound transmitters and receivers operating at 40kHz were designed in order to maximize the possible range of transmission of the developed system. Prototype of the ultrasonic transmitter and receiver system was developed and tested using 400EP18A (transmitter and receiver transducers) and 400PT160 (transmitter and receiver transducers) manufactured by Pro-Wave

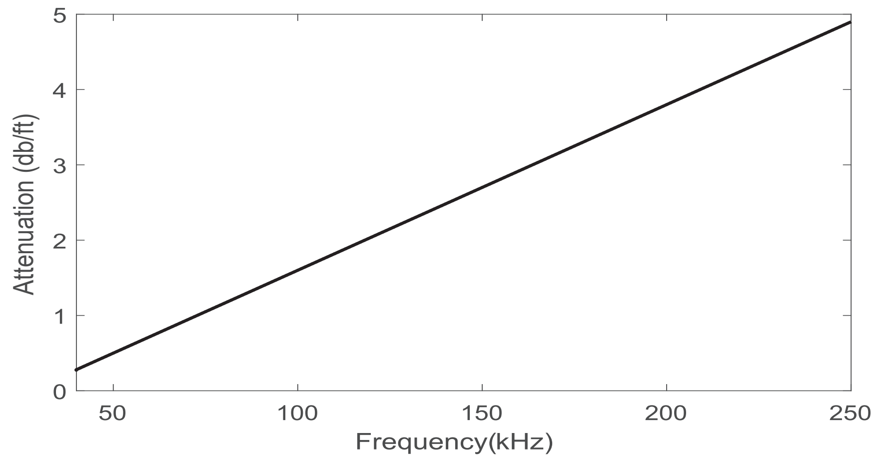


Figure 4.2. Attenuation of ultrasound signal with frequency

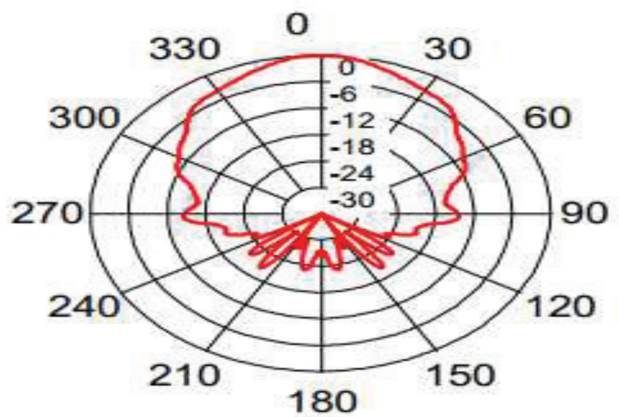


Figure 4.3. Beam angle of 400EP18A ultrasonic transducer [93]

Electronics Corporation [93]. Both transducers have a bandwidth of 2kHz. As indicated in Figure 4.3, 400EP18A transducer provides a wider horizontal beam of 120°. The commonly available 400PT160 transducer (also operating at 40 kHz) provides a horizontal beam width of 60°. The receiving sensitivity at 0 dB for 400EP18A and 400PT160 is -75dB and -65dB respectively. The schematic diagram of the designed ultrasonic transmitter and receiver is shown in Figure 4.4 and Figure 4.5 respectively.

The transmitter circuit receives 40± 1kHz input frequency from the central unit. Two sets of three inverters each, connected in parallel configuration as shown in Figure 4.4 is utilized to increase the power of transmission of the transmitter. The phase of the voltage applied to the positive terminal

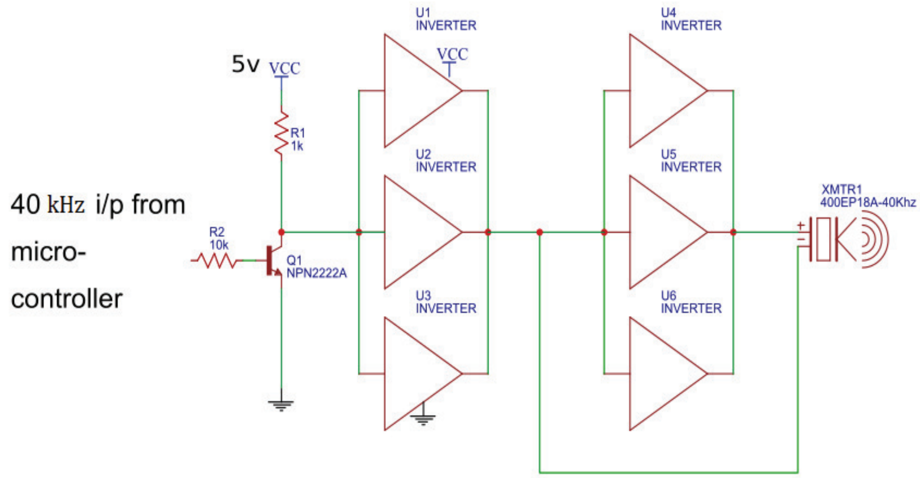


Figure 4.4. Ultrasonic transmitter circuit

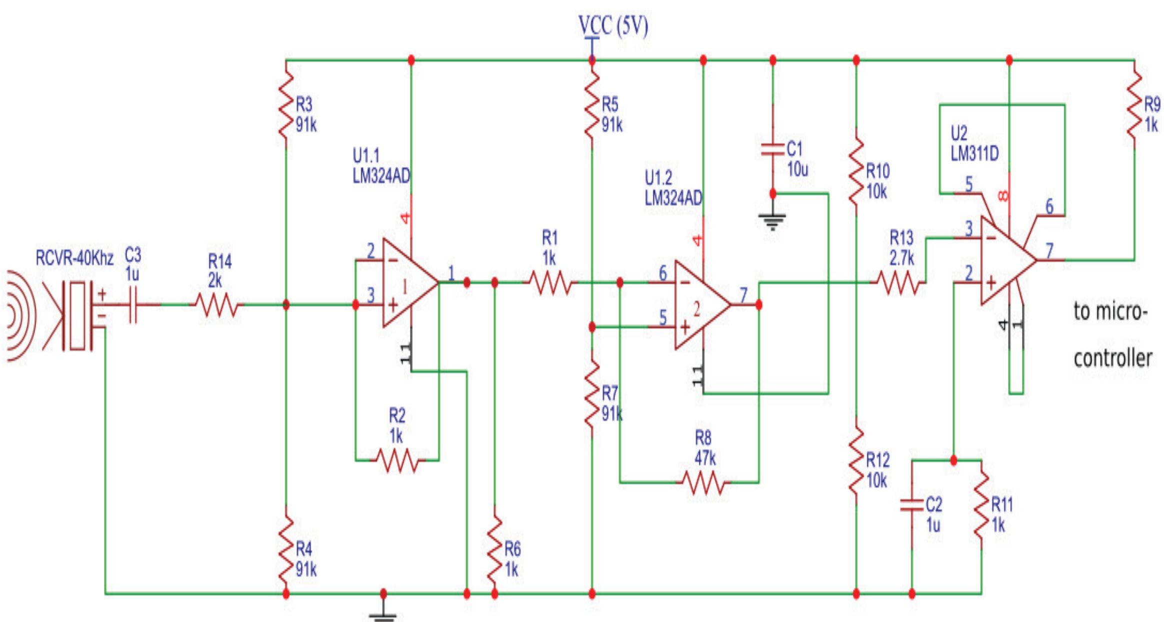
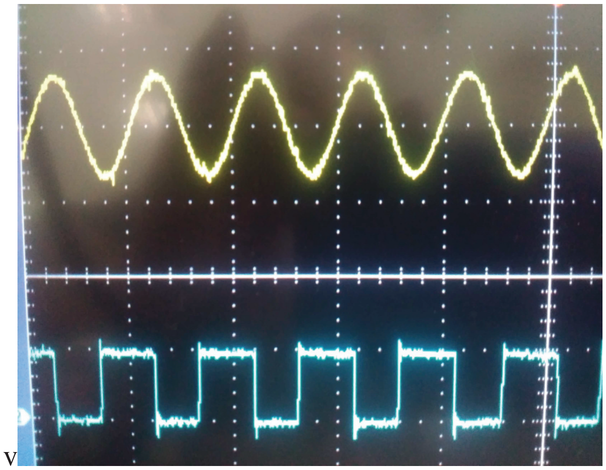


Figure 4.5. Ultrasonic receiver Circuit



v

Figure 4.6. Signal at top- Ultrasonic signal output received at receiver (Y-axis-1 square= 1V), Signal at the bottom -Transmission frequency 40kHz generated by central unit, Y-axis unit- 1 square= 5V units

and the negative terminal of the transducer has a 180° shift, because of which the voltage applied to ultrasonic transducer for transmission is twice the voltage applied to the input of the inverter. The input stage of the ultrasonic receiver is a bandpass filter designed using LM324 operational amplifiers which ensures that signals within the frequency band of 40±1kHz are detected by the receiver circuitry. The signal received at the output of the filter stage (pin 7 of Figure 4.5) when the transmitter and receiver is placed at a distance of 4 meters is shown in Figure 4.6. The last stage of the ultrasound receiver designed using LM311 is a wave shaping circuitry, which converts the output signal of the filter stage to a square pulse which can be fed to the central unit. When ultrasonic signal is not received at the target node, the output of the ultrasonic receiver is maintained at a logical "high" state. The ultrasound transceiver circuitry provides a successful communication range of up to 8 meters, when the transmitter and receiver are placed along a straight line at the same height, oriented towards each other in LOS condition. Prototype of ultrasonic transmitter and receiver system was implemented only to test the accuracy of time of flight measurements. Hence, obtaining a broader transmission angle and wider coverage is not considered in the scope of this work.

Central Unit:

The central unit is the perception module as described in Section 3.4.1. The preception module is built with STM32F4 discovery board which utilizes, 32-bit ARM based STM32F407VGT6 microcontroller. The perception module has CC2500 radio module from Texas Instruments for

RF wireless communication. The central unit is interfaced with the ultrasonic unit via the General Purpose Input/Output (GPIO) pins. The timer peripheral of the microcontroller in the central unit provides the ultrasonic transmitter with 40±1kHz square wave for beacon transmission. Similarly, the output of the ultrasonic receiver is also interfaced to the GPIO pins of the microcontroller. The central unit of the target nodes and the beacon nodes are fitted with a room temperature sensor (DHT22 temperature sensor with an operating temperature range of -40°C to 80°C and an accuracy of ± 0.5°C [94]) and hence along with the timestamps, temperature measurements are also recorded by the nodes.

4.2.1 Localization Procedure

A fine-grained or range-based indoor localization scheme is presented in this thesis. Fine-grained localization is generally implemented in two steps:

1. Estimation of distance between the target and beacon nodes.
2. Estimation of location of the target.

A localization scheme which utilize Time of Arrival (ToA) technique is presented in this chapter. Time Difference of Arrival (TDoA) is the most widely utilized technique used for estimation of distance between the target and beacon node. Popular indoor localization system 'Cricket' utilize Time Difference of Arrival (TDoA) between an ultrasonic and RF signal for distance estimation between the target and the beacon node [71]. TDoA is widely utilized for distance estimation between target and beacon node, as the time synchronization between the target and beacon node is not required for TDoA based distance estimation. In TDoA, the beacon node transmits RF signal along with the ultrasonic signal to the target node. Assuming that RF signals are received instantaneously, the difference in time recorded at the target node on the reception of ultrasound and RF signal is utilized to measure the distance between the target node and the beacon node. Previous studies have identified that ToA technique is more accurate than TDoA, however, time synchronization is a prior requirement for the implementation of ToA technique [95]. As mentioned in Chapter 3, most of the techniques available in literature for synchronization implement either time offset compensation or frequency offset compensation only. The techniques for time offset compensation available in literature requires two-way messages and frequency offset compensation require frequent communication for offset compensation. Hence, TDoA technique was preferred for distance estimation. From the studies presented in Chapter 3, it can be concluded that the inherent delays and uncertainties introduced by the RF radio module and the wireless channel should be removed carefully from the timestamp measurements before the timestamps are utilized for distance estimation in available ultrasonic based localization systems.

In this thesis, Time of Arrival (ToA) of the ultrasonic signal between the target and beacon node is utilized for the position estimation. Only instantaneous synchronization between the target and beacon nodes is required for the recording of ToA measurments by the central unit. Instantaneous synchronization can be achieved using time offset compensation. Having achieved accurate time offset compensation through one-way messages, as presented in Chapter 3, we re-evaluate the suitability of ultrasound ToA based beacon localization scheme for obtaining localization accuracy in the order of few centimetres in indoor environments . The localization is implemented in two steps- Distance estimation, Position estimation.

4.2.1.1 Distance Estimation

ToA techniques rely on the Time of Flight (ToF) or time of travel measurement of the transmitted signal between the beacon node (transmitter) and the target node (receiver). The distance between the target and beacon nodes is calculated by multiplying the velocity of signal and the measured ToA values. If beacon nodes B_1, B_2 and B_3 are placed at known locations, (x_n, y_n) where x_n and y_n are the x and y coordinate value of the n^{th} beacon as in Figure 4.7, then based on ToA of the signal, the position of the target node (x, y) can be calculated by solving the equtions given below.

$$(x - x_1)^2 + (y - y_1)^2 = d_1^2 \tag{4.2}$$

$$(x - x_2)^2 + (y - y_2)^2 = d_2^2 \tag{4.3}$$

$$(x - x_3)^2 + (y - y_3)^2 = d_3^2 \tag{4.4}$$

where 'd_n' is the distance between target node and n^{th} beacon. The method described above is referred as trilateration.

If ToA is calculated based on RF signal, then for estimating the distance with a resolution of 1cm, the basic clock tick required is $\approx 330ns$ (since velocity of RF signal is $\approx 3x10^8$m/s). In low cost networks, clock ticks are in order of 'μs' and hence RF signal cannot be used to measure the distances with a resolution in order of few centimeters. For SRS or MRS, localization precision in the order of a few centimeters is desired. Ultrasonic signals travel at a much lesser speed ($\approx$330m/s) when compared to RF signals and hence ToA of ultrasound signals is utilized instead of using RF signals in the presented localization scheme.

The timestamping for ToA measurement is performed by the central unit. The ToA measurements are obtained using the proceedure described below.

1. A beacon node broadcasts an RF message requesting the target nodes to listen for localization messages. On the reception of the message, by the central unit of the target nodes, they disable the peripheral interrupts till the ToA measurement is completed. The target node also resets the Real Time Clock (RTC) of STM32F407VGT6 microcontroller of the central unit and the target node becomes static. The disabling of peripheral interrupts and resetting of the RTC is performed to ensure accurate time offset compensation, as explained in Section 3.4.2.

2. The beacon node then broadcasts three RF 'tsync' messages to perfom time offset compensation of the target nodes as mentioned in Section 3.4.2. Once the time offset between the target and the beacon node is estimated by the target node, target node updates its RTC based on the measured offset, thus performing time offset compensation.

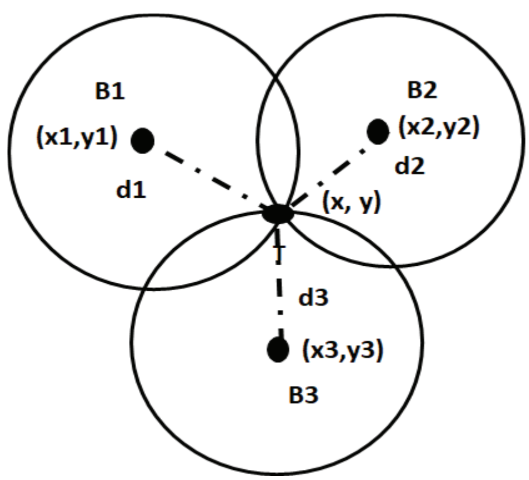


Figure 4.7. Deployment of target and beacon node for trilateration

3. The time synchronized target node then polls the GPIO pin connected to pin 7 (Refer LM311 of Figure 4.5) of the ultrasonic receiver unit. On receipt of the ultrasonic beacon signal from the beacon node, a square pulse will be generated at the output of the ultrasonic receiver. The central unit of the target nodes record the timestamp (T_r) on the first falling edge signal from the ultrasonic receiver. The transmit time (T_t) which is recorded by the central unit of the beacon is transmitted to the target node using an RF message.

4. Once the timestamping is complete, the target node calculates the time of flight (T_n) where 'T_n' is the time difference between the reception time of the ultrasonic signal at the target node (T_r) and the transmission time of the ultrasonic signal (T_t) at the n^{th} beacon.

An important advantage of the proposed ToA estimation scheme is that the nodes in the system, are not required to be globally synchronized with respect to time. Steps 1-3 are repeated by other two beacons and in-response, step 4 is performed by the target node.
The central unit of the target node performs timestamping at the first falling edge of the ultrasonic signal. Since the time of flight of multipath components is always longer than the direct path; compensation for multipath signal reception is not required to be performed on timestamps. The ultrasonic beacon transmissions are staggered by an interval of 40ms (the staggering interval is based on the range of beacon signal and the area of the deployment). The work was tested in a 4m x 4m area (40ms is approximately equal to a travel distance of 13m) so as to avoid the interference of reflected ultrasonic signals in the recorded time. From the ToA measurement, distance between the target node and beacon node under LOS condition can be estimated as

$$T_n * V_s = d \tag{4.5}$$

where 'd'' is the Euclidean distance between the target node and the beacon node and V_s is the velocity of ultrasound signal in air. The major factors affecting the velocity of sound in air are temperature and humidity. The velocity of sound in air can be expressed as

$$V_s = (331.296 + (0.606 * \theta)) * (1 + RH * 9.604 * 10^{-6} * 10^{(0.032*(\theta-(0.004*\theta^2)))}) \tag{4.6}$$

where 'θ' is the temperature and 'RH' is the relative humidity [96]. From equations (4.5) and (4.6), it can be inferred that the relative humidity needs to be considered only if sub-millimetre accuracy is required in positioning. Hence the velocity of sound in air can be approximated as

$$V_s \approx (331.296 + 0.606 * \theta) m/s \tag{4.7}$$

Since the proposed time-offset compensation scheme and ToA estimation involves only one-way messages from beacon to target nodes, the ToA measurement of all target nodes within the range of beacon can be performed simultaneously using the presented time of arrival measurement technique.

4.2.1.2 Analysis of Position Estimation using Trilateration

The ultrasonic transmitter receiver system was tested in an indoor room of area of 4m x 4m under ideal Line-of-sight (LOS) conditions between the target node and the beacon node. The objective of the experiment was to test the accuracy of ToA measurements using the designed hardware. The localization hardware including the central unit and the ultrasonic unit is mounted on the beacon and target robot (Refer Appendix B). The beacon nodes B_1, B_2 and B_3 were positioned at (x=0, y=0), (x=4m, y=0m) and (x=2m, y=4m). Target node was kept at random positions in the 4m x 4m area at an height of 0.5 meter. Once 'd_n', the distance between the target node and the n^{th} beacon node is measured after the ultrasonic beacon transmissions, the two-dimensional location of target node (x, y) with reference to the beacon nodes was obtained using trilateration by solving equations (4.2) - (4.4). The position estimated using trilateration under the LOS condition for 10 target positions is presented in Table 4.1.
The three major sources of error in ultrasound based localization can be identified as

1. Error in time of flight (ToF or ToA) measurement mainly due to the error in time synchronization.

2. Error in converting ToA to distance - The time of flight measurement is incorrectly converted to distance without taking into consideration the factors which affect the velocity of sound, i.e predominantly the environmental temperature.

3. ToA is recorded correctly, but the distance represented by the timestamps cannot be calculated using equation (4.5) due to the NLOS between the beacon and the target node.

The maximum error reported in ToA estimations during repeated experimentations is 13μs and for 90% of trials, the error is $\leq$ 10μs. For any given temperature of the range, 15°C-35°C, variation in 10μs will lead to a maximum variation in distance measurement of only $\approx$0.2cm according to equation (4.7). Hence, the proposed localization scheme is accurate for localization under LOS conditions. The major source of error in ultrasound based positioning is then due to NLOS conditions between target and beacon node. The NLOS conditions will be significant in indoor applications due to the presence of dynamic obstacles between target and beacon node. It can be observed that $\approx$30cm error in (x, y) position is reported in Table 4.1 even in the absence of obstacles between the target and beacon node. It has to be noted that with the hardware, the error in timestamping is limited to a maximum value of 13μs. Estimating the location using trilateration (equations (4.2)- (4.4)) will lead to significant error in the calculated position due to the data type restrictions of the microcontroller utilized for performing the trilateration. The observed error up to $\approx$ 30cm for LOS conditions is due to the data type restrictions of the microcontroller in performing the trilateration operation. Most of the advanced microcontrollers including the STM32F407VGT6 microcontroller (in the central unit-Figure 4.1) used for performing trilateration in the experiment,

Actual (x,y) position of Target node in LOS conditions (m)	**Estimated target node (x,y) position using Trilateration (m)**
(2.0, 3.4)	(2.06, 3.47)
(1.2, 3.0)	(1.01, 2.96)
(.2, 2.6)	(0.76, 2.29)
(2.6, 3.4)	(2.17, 3.52)
(2.2, 0.6)	(2.82, .69)
(1.90, 3.0)	(1.90, 3.04)
(3.2, 3.4)	(3.26, 3.40)
(1.2, 3.8)	(1.25, 3.83)
(1.2, 3.5)	(1.48, 3.51)
(2.5, 1.3)	(2.51, 1.38)

Table 4.1. Target node position calculated using Trilateration

has only a single precision FPU and hence, will lead to error in location estimation. Trilateration technique cannot be utilized for location estimation under NLOS conditions, even if one of the three beacons are affected by NLOS. Hence, having demonstrated the proof of concept of recording accurate time of arrival measurements using the hardware, a novel artificial neural network based scheme for location estimation from the time of arrival measurements, which is suitable for localization under LOS and NLOS conditions is developed and described in Section 4.3.

4.3 Location Estimation in LOS/NLOS Conditions

Techniques such as trilateration which utilize the mathematical modelling of nodes placed along a triangle, fail to account for the NLOS conditions between beacon node and the target node. The amount of positive bias on timestamp measurements due to the presence of obstacles between the beacon and the target node, variation in timestamp measurements due to the variation in reflection coefficient of the obstacle, orientation of beacon and target node relative to the obstacle, etc. is difficult to be estimated and then accounted for using mathematical modelling. As mentioned in Chapter 2.2 and Section 4.1, a few ILS systems which take into account the effect of NLOS conditions are available. Techniques that utilize machine learning for identification of NLOS conditions (as mentioned in Section 2.2.4.2), for UWB based localization systems, usually perform offline learning of NLOS conditions in the area of deployment and then mitigate measurements affected by NLOS during the localization process. It is difficult or nearly impossible to capture a comprehensive data set, including all the possible NLOS conditions in indoor environments. A Bluetooth and Ultrasound Platform for Mapping and Localization (ALPS) developed in 2015, require LOS between at least three beacons and the target node in order to accurately determine the position of the target node [70]. When beacons are blocked by obstacles, the ALPS system estimates the position based on inertial data from the phone and filters out the measurements affected by NLOS using an Support Vector Machine (SVM) classifier that checks the ratios between Bluetooth RSSI, ultrasonic signal strength and ultrasonic time of flight measurements. The performance analysis of the ALPS system indicates that even when 1200 samples of measurements affected by NLOS measurements were utilized for training, the system was able to identify NLOS and estimate the position of target node with an accuracy of 100 cm and 80% precision only [70]. As an alternative approach, in certain ILS systems, a large number of beacon nodes are utilized to ensure that at least a few beacons are in LOS with respect to the target node. A sufficient number of NLOS free beacon measurements are then selected for location estimation based on the desired accuracy. Casas et.al has utilized Least-Median of squares (LMedS) method to reject NLOS affected measurements when location estimation is being carried out [56]. However, the system necessitates the presence of a large number of beacon nodes for localization of target node. For ensuring quick deployment of robotic systems, it is essential that the localization scheme incurs minimal offline calibration. To reduce the cost of deployment and also to reduce the number of wireless messages required for localization, it is desired that the localization scheme utilizes a minimal number of beacons.

In this thesis, an Artificial Neural Network (ANN) based scheme is presented for two-dimensional (2D) location estimation in LOS and NLOS conditions. The proposed scheme provides the 2D position of the target node using the time of flight/arrival (ToA) measurements from 3 beacon nodes. The unique characteristics of the proposed scheme is that the artificial neural network is required to be trained only under LOS conditions. The system provides reliable accuracy under LOS conditions. The system also identifies the timestamps affected by single NLOS (NLOS between one target and beacon node) and estimates the (x, y) position of the target node using the other two ToA meaurements which are not affected by NLOS.

In the overall architecture of the localization system presented in Figure 4.1, the input to the location estimation unit are the time difference of flight measurements between the three beacon(s) and the target node. The two stage ANN based location estimation unit will compute the (x, y) position of the target node based on the received time of flight measurements.

4.3.1 Artificial Neural Networks- Brief Introduction

Artificial Neural Networks (ANNs) are data processing systems, consisting of a large number of interconnected processing elements (artificial neurons) in an architecture, inspired by the structure of cerebral cortex of the brain. ANNs have been proposed by researchers for solving complex engineering problems that are extremely difficult to be modelled with mathematical equations. Soft computing techniques such as artificial neural network based computing are generally robust to imprecision, uncertainty and partial truth. ANNs exhibit mapping capabilities, i.e, they can map input patterns to their associated output patterns. Hence, ANNs can be trained with known examples of a problem, before they are tested for their 'inference' capability on unknown instances of problem. ANNs also have the ability to generalize, thus they can predict new outcomes from past trends. The implementation of neural networks on hardware is a research area which has progressed in the recent years. Several hardware implementations of MLF has been achieved by researchers in the past decade [97–99]. Artificial Neural networks are already in use for task planning, path planning, and control of robots.

ANNs are broadly classified into three categories- single layer feed-forward networks, multilayer feed-forward networks and recurrent networks [100]. The basic component of an ANN is a neuron. A neuron with 'm' inputs is shown in Figure 4.8. In a neuron, each input is weighted with an appropriate weight 'w' and the sum of weighted inputs and the bias is applied as the input to a transfer function. The output of neuron can be described as follows:

$$output = f(\sum_{i=1}^{m}(w_i * x_i)) + bias \tag{4.8}$$

Any transfer function which is differentiable can be utilized to generate the output of the neuron. However the Linear, Hyperbolic tangent sigmoid (tansig) and the Log-sigmoid (logsig) transfer functions are the most popular ones.

Single layer feed-forward networks consist of two layers, namely input and output layer. The input layer receives the input signals and the output layer consisting of neurons generates the output signals. Computations are performed only in the output layer. Single layer feed-forward networks

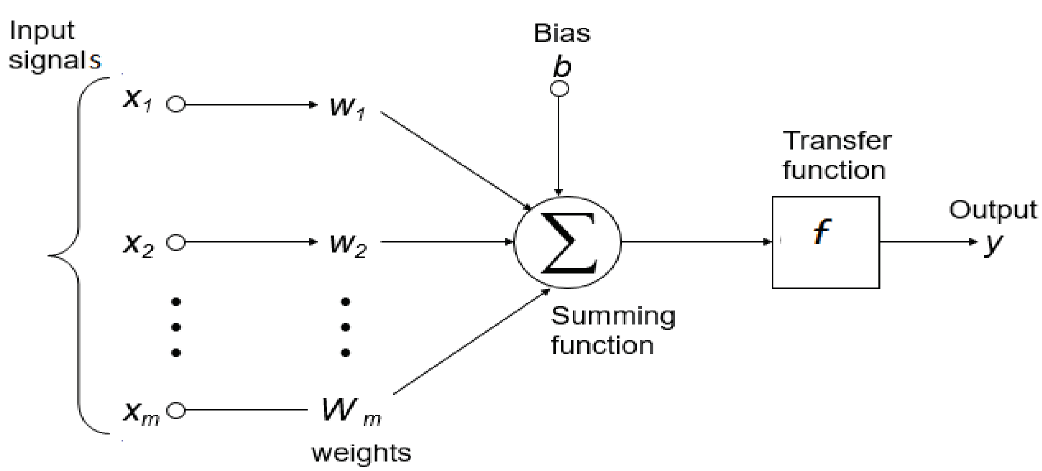


Figure 4.8. Architecture of a neuron [100]

due to their simpler structure can represent only linearly separable data accurately. A multi layer feed-forward (MLF) neural network consists of neurons, that are organized as multiple layers. The network consists of an input layer of source signals, at least one middle or hidden layer of neurons, and an output layer of neurons. The structure of a MLF is shown in Figure 4.9. Recurrent networks differ from the feed-forward network architectures in that, there is at least one feedback loop from output to the previous layers. The recurrent networks are memory intensive when implemented in hardware. In this thesis, MLF neural network architecture is utilized for location estimation as they can represent the nonlinearity in data and are less hardware intensive when compared to recurrent networks.

The MLF network operates in two modes- training and prediction. For training and prediction using a MLF neural network, two data sets- the training set (data set required for training the neural network) and test set (the data set required to verify the accuracy of MLF prediction) are required. The network can be trained for function approximation (nonlinear regression), pattern classification, or pattern association using various learning techniques. Learning techniques utilized for training of ANN can be broadly classified into two types: Supervised Learning, in which the output of ANN is known beforehand and Unsupervised learning in which the output of ANN is not known in advance. In this work, supervised training is utilized. During training, the weights and biases of the neural network are iteratively adjusted to minimize the network performance function.The most commonly used performance function for feedforward networks is the mean square error (MSE),

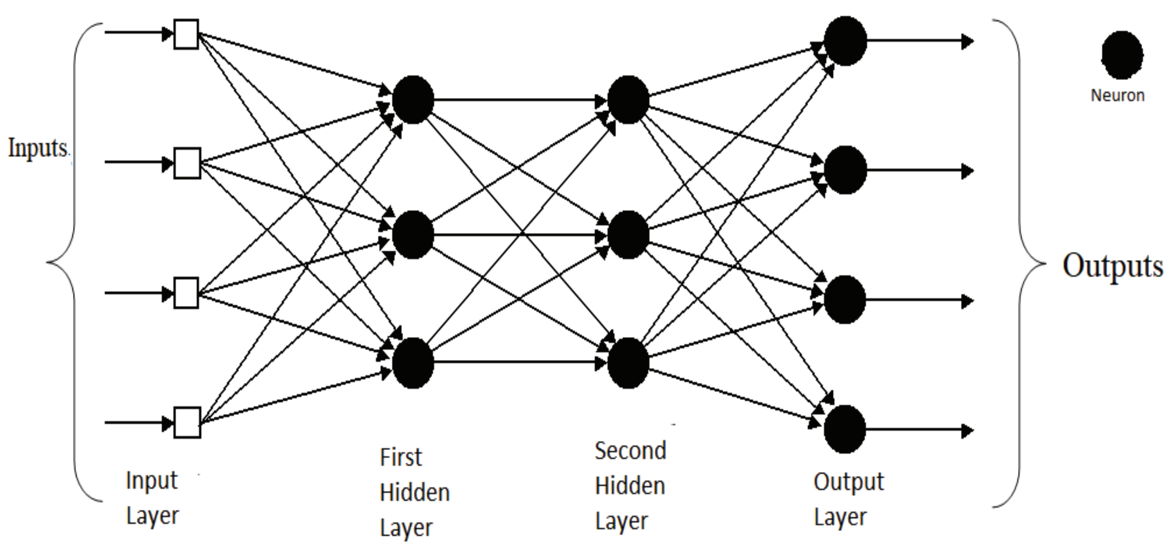


Figure 4.9. Architecture of a multi layer feed-forward (MLF) network

i.e the average squared error between the network outputs and the target outputs. The training mode begins with arbitrarily assigned values for weights of the neurons in each layer of network and proceeds iteratively. Each iteration of training is referred as an epoch. In each epoch, the network adjusts the weights in the direction that reduces the MSE error. After several epochs, the weights and bias will gradually converge to the locally optimal set of values.

Several training algorithms are available for supervised learning of feedforward networks. In the work presented in this thesis, the neural network toolbox (NN toolbox) available in MATLAB was used for the simulation of ANN. Most of the popular ANN learning algorithms are available as inbuilt functions in NN toolbox [101]. Hence, only a brief overview of the supervised learning algorithms are presented here. Most of the algorithms use the gradient of the performance function to determine how the weights are adjusted so as to minimize the error. The gradient is determined using a technique called backpropagation, which involves performing computations backwards through the network. The simplest implementation of backpropagation learning (eg: Gradient Descent (GD) algorithm), updates the network weights and biases in the direction in which the performance function decreases most rapidly, i.e the negative of the gradient. The weights and biases are updated in the direction of the negative gradient of the performance function. Gradient Descent with Momentum (GDM) algorithm provides faster convergence when compared to GD. However, GD and GDM are extremely slow for online training. The learning algorithms based on heuristic techniques such as Resilient Backpropagation (RP) are faster algorithms. Another other category of fast learning algorithms utilize numerical optimization techniques such as conjugate gradient, Quasi-Newton, and Levenberg-Marquardt. The basic backpropagation algorithm adjusts the weights in the steepest descent direction (negative of the gradient) in GD learning algorithm. Even if the function decreases most rapidly along the negative of the gradient, this does not necessarily produce the fastest convergence. In the conjugate gradient algorithms, a line search is performed along conjugate directions, which produces generally faster convergence than steepest descent directions. Line search is computationally expensive, since it requires that the network response to all training inputs be computed several times for each search. The scaled conjugate gradient algorithm (SCG) avoids the time-consuming line search. Levemberg-Marquardt (LM), Scaled Conjugate gradient Backpropagation (SCG), Broyden–Fletcher–Goldfarb–Shanno quasi-newton backpropagation (BFGS) are widely accepted algorithms for supervised learning [102]. Levenberg-Marquardt algorithm provides the fastest training of the network, however the memory requirements of LM is highest among the above-mentioned learning algorithms [103]. The conjugate gradient algorithms are particularly suited for networks with a large number of weights. The SCG algorithm is almost as fast as the LM algorithm and at the same time has relatively modest memory requirements. Gradient descent is generally preferred for large neural networks, whereas the Newtons method is computationally very complex, requiring inverse matrix operations [104]. A detailed description of the different learning algorithms for supervised learning is available in [101].

Several design decisions are to be made before utilizing a MLF for any practical application. The accuracy of ANN based location estimation technique depends on the type of neural network architecture, the number of neurons in the architecture, and the type of transfer function utilized. Even though the proposed scheme is validated through simulations in this work, an appropriate architecture with minimal memory requirements and processing requirements has to be selected for the implementation of the architecture on robot hardware. The choice of training algorithm utilized to train the network also has an impact on the accuracy of location estimation. The training of MLF has to be done such that the network generated after training is generalised. A network is said to be generalised when the input/output relationship computed by network is correct (with acceptable error, depending on the application) for those input/output patterns which were not utilized for training the network. The size of training data and choice of input/output patterns is an important factor which affects the performance of the neural network. The training set must be a representative subset of the set of all cases that the network should generalise to. Hence the choice of appropriate training data set is a crucial decision to be made .

Another important design parameter for MLF networks is the selection of number of hidden layers in the network. Universal approximation theorem states that "the standard multilayer feed-forward network with a single hidden layer, which contains finite number of hidden neurons, is a universal approximator among continuous functions, under mild assumptions on the activation function" [105]. Universal approximation theorem, recommends using one hidden layer for NN and then suggests the testing of performance of neural network for varying number of neurons in the hidden layer. If the network is not generalised even after using a large number of hidden neurons, then introducing another hidden layer or changing the neural network architecture may be considered.

The performance of a neural network is evaluated based on the following metrics: Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Average Error (MAE) and Coefficient of

Correlation or determination (R^2). For the location (position) estimation problem addressed in this chapter, these metrics can be defined as follows.

1. **Mean Square Error** (MSE)

$$MSE = \frac{\sum_{i=1}^{n}(predicted\ position - actual\ position)^2}{n} \tag{4.9}$$

2. **Root Mean Square Error (RMSE)**

$$RMSE = \sqrt{M}SE \tag{4.10}$$

3. **Mean Average Error (MAE)**

$$MAE = \frac{\sum_{i=1}^{n}(|predicted\ position - actual\ position|)}{n} \tag{4.11}$$

4. **Coefficient of Correlation (R^2)**

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(predicted\ position - actual\ position)^2}{\sum_{i=1}^{n}(actual\ position)^2} \tag{4.12}$$

The ideal value for MSE, MAE, RMSE is zero and R^2 is 1.

4.3.2 Robust Location Estimation Unit using Two Stage ANN

To determine the location of an object or robot from the time of flight of ultrasonic signal between the beacon and the target nodes, it is critical to identify the presence of NLOS conditions in the time of flight measurements. Otherwise, the estimated location using NLOS affected measurements will be significantly incorrect. As mentioned in Section 4.1, the available machine learning based techniques that take into account, localization under NLOS conditions, perform offline training of system under various NLOS conditions to detect and remove the NLOS affected measurements. As mentioned in Section 4.1, the accuracy of these systems in location estimation is in the order of meters. It is time consuming and extremely cumbersome to obtain a comprehensive data set which represent the possible NLOS conditions, in indoor environments. In this section, an ANN based

Location Estimation Unit (ANN-LEU), designed for the 2D location estimation of target nodes or robots is presented. A unique characteristic of the proposed scheme is that the training of the ANN is required to be performed only under LOS conditions. Hence the system can be easily trained in different environments, enabling quick deployments.

It is desired that in the proposed localization scheme, the target robot can position itself based on a minimum number of beacon nodes. Hence, inspired by the principle of trilateration, a location estimation scheme which utilizes 3 beacon nodes is designed for localization. However, the system can also perform accurate localization using NLOS free, time of flight measurements from 2 beacons under certain conditions, as will be demonstrated in this section. As mentioned in Section 4.3, the input to the location estimation unit are the time difference of flight measurements between the three beacon nodes and the target node. The two stage ANN based location estimation unit computes the (x, y) position of the target node based on the time of flight measurements. The functionalities of the two stages of ANN are

- Stage 1 ANN: Estimation of two-dimensional position (x, y) of the target node.
- Stage 2 ANN: Detection of NLOS and Validation of position estimated using Stage 1

4.3.2.1 Dataset Generation for Training of ANN

The performance of ANN-based location estimation unit has to be tested under different NLOS and LOS conditions. Since the generation of large data set under NLOS with hardware was a cubersome process, a room acoustic simulator, **Locusim** (or also referred as Locus simulator) was utilized to simulate the ultrasonic transmissions. This simulator was developed by Albuquerque et.al [106] in order to analyze the behaviour of ultrasonic signals in controlled environments. Using Locusim simulator, ultrasonic transmission between the target nodes and beacon nodes can be simulated and the time of flight of ultrasonic signal between the transmitter and receiver can be recorded. The simulator accounts for wall reflections, sound attenuation, effect of temperature and humidity on the ultrasound beacon signal and allows configuration of the transducer beam characteristics. By default, the transducer is configured for omnidirectional transmission.

An indoor arena of 4m x4m was modelled with a floor, ceiling and 4 walls using the Locusim simulator. The temperature of indoor arena modelled in Locusim is configured for 15°C. As there is a linear relationship between the velocity of ultrasonic waves and temperature, as per equation (4.7), the timestamps recorded at any other temperature is scaled to obtain the time of flight readings corresponding to 15°C before feeding the timestamps into ANN as indicated in Figure 4.1. For the training of ANN, the deployment scenario as shown in Figure 4.10, is modelled in Locusim simulator. Three beacon nodes are placed at locations (0,0), (0,4) and (4,4) respectively. The ultrasonic transmitter/receiver modules of beacon nodes and target nodes are kept at a height of 1m from the ground. In an MRS, the robots themselves can serve as beacon nodes and they can occupy fixed locations in the indoor area when they serve as the beacons. Hence the ultrasonic beacons and receivers are assumed to be at the same height. Time of flight measurements (T_1, T_2, T_3) of the ultrasonic signal between the target node and beacon nodes (B_1, B_2, B_3) were generated for different placements of target node as shown in Figure 4.11 using Locusim simulator. These measurements serve as the training data set for Stage 1 and Stage 2 ANN.

The time of flight measurements at target node for 72 known locations (at least 4 positions for every 1m x 1m) as shown in Figure 4.11 were recorded. The training data set for Stage 1 ANN was generated using 72 set of time of flight measurements (T_{1i}, T_{2i}, T_{3i}) under LOS conditions between target and beacon nodes. The training input data set includes 72 measurements (T_{1i}, T_{2i}, T_{3i}), where ‘i’ ∈ (1-72) , 72 measurements of format (0, T_{2i}, T_{3i}) , 72 measurements of format (T_{1i}, 0, T_{3i}) and

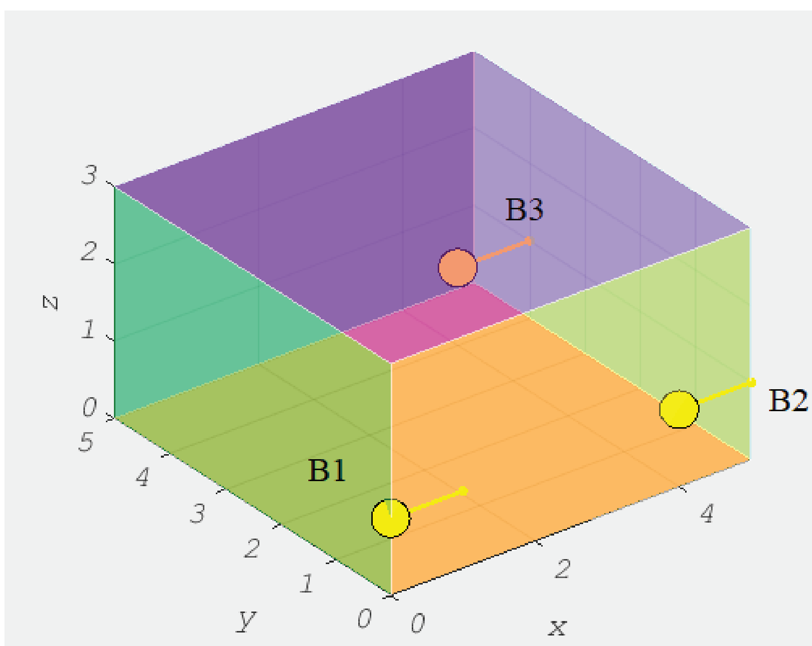


Figure 4.10. Deployment of Beacon nodes in Locusim simulator.

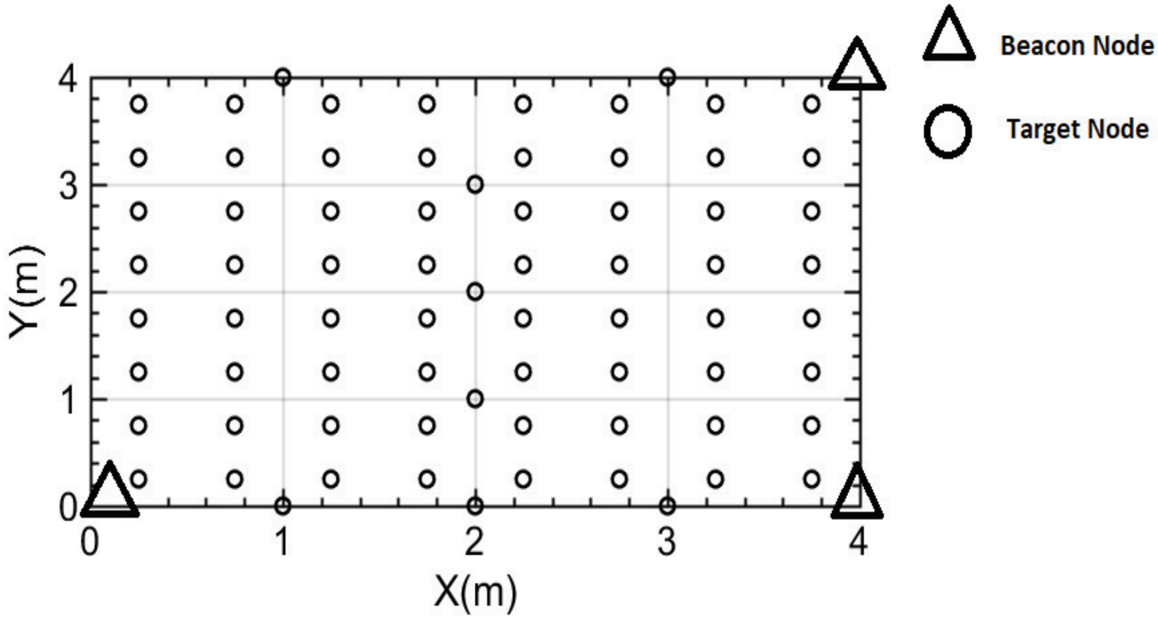


Figure 4.11. Deployment of target nodes for generation of training data.

also 72 measurements of format $(T_{1i}, T_{2i}, 0)$. It can be noted that time of measurement between the beacons and 72 target locations were measured only once and the other 72x3 set of measurements were obtained as mentioned above. The output data set for the training of Stage 1 ANN are the corresponding target positions $(x_i,\ y_i)$ for all 4 sets of 72 measurements.

Stage 2 ANN was trained using the 72 known $(x_i,\ y_i)$ positions (as shown in Figure 4.11) as input and the corresponding (T_{1i}, T_{2i}, T_{3i}) as the output. Hence the trained Stage 1 ANN can generate (x, y) position outputs if time of flight measurements from three beacon nodes, free from NLOS are provided as input, or if time of flight measurements from two beacons free from NLOS are provided as input. The trained, Stage 2 ANN can provide the time of flight measurements corresponding to the target node position in $(x_i,\ y_i)$ under LOS conditions.

All (x, y) positions are mentioned in this chapter in lq meters' unless otherwise specified. The time of flight measurements in this chapter are mentioned in lq milliseconds' unless otherwise specified.

4.3.2.2 Selection of ANN Architecture for Location Estimation Unit

Design of multi-layer feed-forward ANN involves making appropriate choice of following parameters.

- Number of input/output patterns in training data set.
- Type of multi layer feed-forward architecture.
- Number of neurons in the hidden layer.
- Type of Learning algorithm.
- Transfer function of the neurons at the hidden and output layer.

Two types of MLF neural network architectures are considered for the Stage 1 and Stage 2 of ANN-LEU. The architectures are:

- Feed-forward Back propagation network (FFB)
- Cascaded Feed-forward Back propagation network (CFB)

A typical MLF architecture includes an input layer of source signals, at least one middle or hidden layer of neurons, and an output layer of neurons. This typical MLF architecture is also referred as the Feed-forward Back propagation network (FFB) architecture. FFB have been already implemented in hardware by several researchers [99, 102] and CFB is only a minor modification of the FFB implementation. CFB network is similar to FFB network. However, in CFB there is a connection from the input and every previous layer to the following layers. FFB and CFB networks are feed forward in nature and are generally best suited to be trained using back propagation algorithms, hence these networks are termed as feed-forward or cascaded feed-forward back propagation networks. In earlier days, the neural networks were trained offline and the trained network was implemented on hardware. However, with the advancements in microprocessor and FPGA architectures, these neural networks can be trained online on various hardware platforms [107, 108]. In this thesis work, the ANN stages in location estimation unit are simulated using neural network toolbox supported in MATLAB.

The preferred transfer function for the function approximation problems are the 'Tan-sigmoid' transfer function for neurons at hidden layer and the 'Linear' transfer function for the output layers [109]. A linear transfer function can be utilized when no thresholding of output is required. The hidden layer neurons should not be used with linear transfer function. If linear transfer function is used in hidden layer, output of the network will be a linearly seperable solution. In other words, irrespective of the number of hidden layers in the network, the whole network can be represented as a single layer, as combination of linear functions in a linear manner is always another linear function. Among the non-linear transfer functions, sigmoid and tan-sigmoid are the most popular ones. Sigmoid transfer function maps the output of neuron between '0' and '1'. The tan-signmoid transfer function maps the output of neuron between '-1' and '1'. If sigmoid transfer function is used, for negative input, the output generated will be zero. The lack of output will affect subsequent weights in the network which may not be desirable as it will effectively stop the network from training. For tan-sigmoid transfer function, even for negative values of inputs, the output of neuron will be maintained, allowing subsequent nodes to learn from it. Hence 'Tan-sigmoid' is preferred over sigmoid transfer function to allow larger range of inputs and better training.

According to Universal Approximation Theorem mentioned in Section 4.3.1, one hidden layer was selected for the MLF architecture. LM, BFGS, SCG, RP, GDM learning algorithms as mentioned in Section 4.3.1 are considered for the training of neural network. ANN performance is evaluated for two types of transfer functions for the neurons, i.e linear for output layer and tan-sigmoid for hidden layers as is preferred in function approximation problems. FFB and CFB networks were considered for both Stage 1 and Stage 2 ANN, and the networks were trained using the training data set as mentioned in 4.3.2.1 for different number of neurons in the hidden layers (5-10) and using different learning algorithms. Test data set (70 input/output patterns) containing time of flight measurements between the target nodes placed at random points in the area of deployment and the beacon nodes were used to test the performance of Stage 1 and Stage 2 ANN. The Mean Average Error (MAE) performance of Stage 1 ANN in determining the target location (x, y) and the MAE of Stage 2 ANN in determining the time of flight measurements are shown in Table 4.2. From the table, it can be understood that CFB with 10 neurons in hidden layer and FFB with 10 neurons in the hidden layer provide the least MAE for Stage 1 and Stage 2 respectively. Coefficient of Correlation or determination (R^2) obtained was higher than 0.9 during the testing of ANN with the test data as is desired. Hence, CFB with 10 neurons in hidden layer and FFB with 10 neurons in the hidden layer are selected as appropriate ANN architectures for Stage 1 and Stage 2. The Stage 1 and Stage 2 ANN structure is provided in Figure 4.12 and Figure 4.13 respectively. The performance

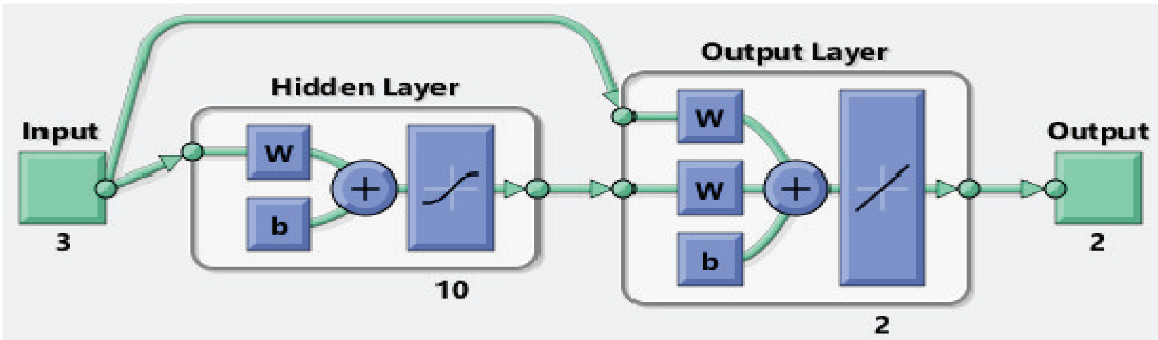


Figure 4.12. Architecture of Stage 1, CFB-ANN

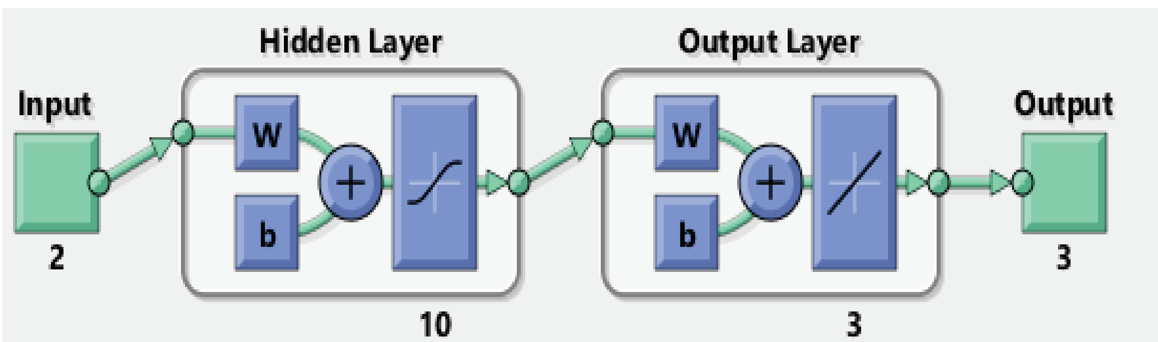


Figure 4.13. Architecture of Stage 2, FFB-ANN

evaluation of Stage 1 and Stage 2 ANN for different learning algorithms (with the same initial value of weights and bias for the architecture while testing different learning algorithms) was performed and the result is presented in Table 4.3. It can be observed from the Table 4.3 that LM learning algorithm takes moderate number of epochs (iteration) for training, at the same time provide the best accuracy. If the training has to be performed on hardware, GDM or SCG learning algorithms may also be considered for training, especially if the system is resource constrained in terms of memory.

4.3.3 Functional Description of ANN based Location Estimation Unit

For accurate determination of the location of an object or robot based on the time of flight measurements of the ultrasonic signal from the beacons to the target node, it is critical to identify

Table 4.2. Performance of FFB and CFB ANN for Stage 1 and Stage 2 for varying number of neurons in hidden layer.

MLF Architecture & No of Neurons in hidden Layer	MAE Stage 1	MAE Stage2
FFB-5	(0.19,0.35)	(0.099,0.090,0.099)
FFB-10	(0.14,0.10)	(0.022,0.025,0.0179)
FFB-15	(0.14,0.17)	(0.070,0.049,.057)
FFB-20	(0.14,0.13)	(0.031,0.048,0.055)
CFB-5	(0.16,0.06)	(0.072,0.071,0.079)
CFB-10	(0.07,.08)	(0.090,0.050,0.043)
CFB-15	(0.10,0.09)	(0.024,0.046,0.033)
CFB-20	(0.11,.10)	(0.031,0.055,0.093)

Table 4.3. Performance of Stage 1 and Stage 2 ANN for different learning algorithms

Training Algorithm	Epoch (Stage 1)	MAE (Stage 1)	Epoch (Stage2)	MAE (Stage 2)
GDM	35	(0.973, 1.44)	7	(0.34, 0.24, 0.31)
RP	61	(0.2, 0.15)	168	(0.18, 0.22, 0.17)
LM	48	(0.07, 0.08)	41	(0.022, 0.025, 0.0179)
SCG	6	(1.48, .22)	81	(0.33, 0.35, 0.35)
BFGS	65	(0.13,0.10)	8	(0.34, 0.24, 0.31)

the presence of NLOS conditions in the time of flight measurements. The ANN based Location Estimation Unit (ANN-LEU) is designed to identify the presence of NLOS conditions in the time of flight measurements and to reliably estimate the position of the target node. The input to the location estimation unit are the time difference of flight measurements (T_1, T_2, T_3) between the three beacon nodes and the target node. ANN-LEU consists of two stages of ANNs. The functionality of each stage of ANN is as follows.

- Stage 1 ANN: Estimation of two-dimensional position (x, y) of target node
- Stage 2 ANN: Detection of NLOS and Validation of position estimated using Stage 1

The ANN-LEU determines (x, y) position of the target node, if time of flight measurements from three beacon nodes, free from NLOS are provided as input, or if time of flight measurements from two beacons free from NLOS are provided as input. To ensure that the system is robust to false position estimation, each set of timestamps are processed through four iterations of Iterative Logic Block (ILB) as shown in Figure 4.14. After four iterations of ILB, if the acceptance criteria for valid position detection is met only in one of the iterations, then the target position is detected as valid. Otherwise the estimated position by stage 1 ANN is invalidated. The ANN-LEU thus determines, if the target position determined by Stage 1 of ANN-LEU is valid or not and thereby discarding any position estimation made by Stage 1 ANN using 2 or more time stamps affected by NLOS conditions.
The overall functionality of the ANN based Location Estimation Unit (ANN-LEU) is described using a flowchart as shown in Figure 4.14. The different steps performed in the location estimation unit of the target node are as follows:

1. Obtain ToA measurements (T_1, T_2, T_3)- Once the central unit receives the control message from any of the beacon node as mentioned in Section 4.2.1.1 for localization, it waits for beacon messages from other two beacon nodes for a stipulated period of time. Central unit inputs the time of flight measurements to the ANN-LEU, if atleast 2 beacons are received within the stipulated time. The timestamp field corresponding to the beacon node from which the beacon is not received is set to zero. Target node position is set as invaid. Set i=0, t=0. (Refer Figure 4.14).

2. The ToA measurements (T_1, T_2, T_3) are verified for any outliers. For eg: in a 4m x4m area, any measurement which is greater than 19 milliseconds (for the deployment of beacon nodes described in Section 4.3.2.1) is clearly affected by NLOS. If there are more than two ToA measurements with outliers, then the ANN-LEU identifies that the target node position cannot be estimated.

3. If there are atleast two ToA measurements which are free of outliers, then the ToA meaurements are fed to Stage 1 ANN of the Iterative Location estimation Block (ILB) as shown as

enclosed in dotted lines in Figure 4.14. Else, the target position cannot be estimated as there is NLOS between more than one beacon node and the target node.

4. The Stage 1 outputs the initial estimate of the position (X_{s1}, Y_{s1}).

5. Estimated (X_{s1}, Y_{s1}) are rounded off to two decimal digits and fed to Stage 2 ANN. Stage 2 ANN computes the corresponding ToA measurements (T_{s1}, T_{s2}, T_{s3}) from (X_{s1}, Y_{s1}).

6. The (T_1, T_2, T_3) at the input of Stage 1 ANN and the (T_{s1}, T_{s2} and T_{s3}) the output of Stage 2 ANN are compared. The acceptance criteria for a valid position detection is as follows. If (X_{s1}, Y_{s1}) detected by Stage 1 ANN is within the boundary i.e. within the 4x4 area for the current deployment (or within the coverage range of the three beacons in general) and if

$$|T_{sj} - T_k| \leq \phi \tag{4.13}$$

except for $T_k = 0$, for 'k, j' $\in 1, 2, 3$, then the position can be valid or acceptance criteria is met. If the acceptance criteria is met, the Count of 't' variable is incremented. 'ϕ ' is fixed based on the analysis of error measurements in Stage 1 and Stage 2 for different test data sets under LOS conditions. The value is set to be 0.6 milliseconds for the proposed ANN-LEU.

7. The iteration of ILB will stop if the acceptance criteria is met in two of the iterations of ILB or if four iterations of ILB are completed. If the acceptance criteria is met in only one of the four iterations, then the estimated target position by the Stage 1 ANN is valid. In the first Iteration, the ILB checks identifies if all the three time of flight measurements (T_1, T_2, T_3) are free of NLOS. Variable 'i' is incremented in each iteration of ILB, the time of flight measurement corresponding to 'i', i.e T_i is made '0' and iteration of ILB is repeated from Step 4. In the second iteration the ILB checks if there is NLOS between target node and B_1. Third iteration of ILB checks if there is NLOS between target node and B_2. Fourth iteration checks if there is NLOS between target node and B_3. If acceptance criteria is not met in any of the four iterations of ILB, then it is assumed that the target position cannot be estimated. Also if the acceptance criteria is met in more than one iteration of ILB, then the detected position is invalidated.

The ANN based Location Estimation Unit (ANN-LEU) can thus determine the (x, y) position of the target node, if time of flight measurements from three beacon nodes free from NLOS are provided as input or if among the time of flight measurements from three beacons, at least two measurements are free from NLOS. However, when the target position is estimated using only two non-zero time of flight measurements (as in step 7) and if one of them is affected by NLOS, then the acceptance criteria may be met even if the estimated position is incorrect (position determined using 2 or more NLOS affected timestamps can lead to the same position as determined using three timestamp measurements in LOS conditions). To ensure that the system is robust to false position estimation, each set of timestamps is processed through four iterations of ILB. If the acceptance criteria is met for more than one iteration of ILB, then the detected position remains invalid.

4.4 Performance Analysis of ANN Based Location Estimation Unit

The performance of the proposed ANN based Location Estimation Unit (ANN-LEU) was evaluated as follows. The time of flight measurements recorded, using Locusim room acoustic simulator, were used for evaluating the performance of ANN-LEU. The time of flight measurements were recorded under the following conditions: Three beacon nodes (B_1, B_2, B_3) were placed at locations (0,0), (0,4) and (4,4) respectively. Target nodes were deployed in 70 random positions in the 4x4 deployment area. For each of the 70 target node positions, time of flight measurements were recorded under the following conditions using Locusim.

- **Test 1:** Target nodes in LOS conditions with respect to all beacons.
- **Test 2:** One obstacle is placed in front of B_1 as shown in Figure 4.15. Height of obstacle (1 m) is configured to be same as that of the target node. This set up also represents the practical scenario in which the other robots in the system emerge as obstacles for the target nodes.
- **Test 3:** One obstacle is placed in front of B_2. Height of obstacle is configured to be the same as that of the target node.
- **Test 4:** One obstacle is placed in front of B_3. Height of obstacle is configured to be the same as that of the target node.

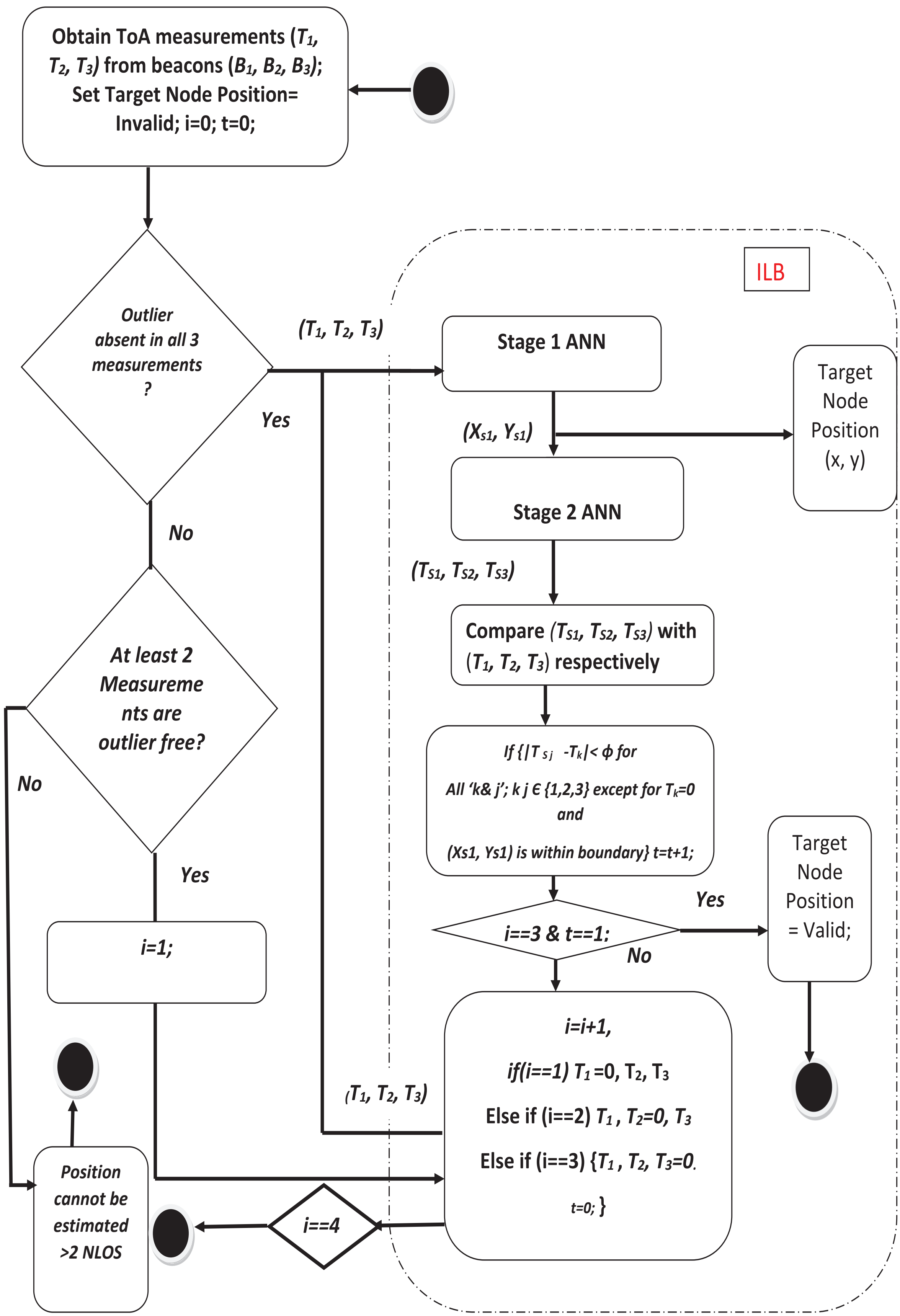


Figure 4.14. Flow chart of the ANN based Location Estimation Scheme.

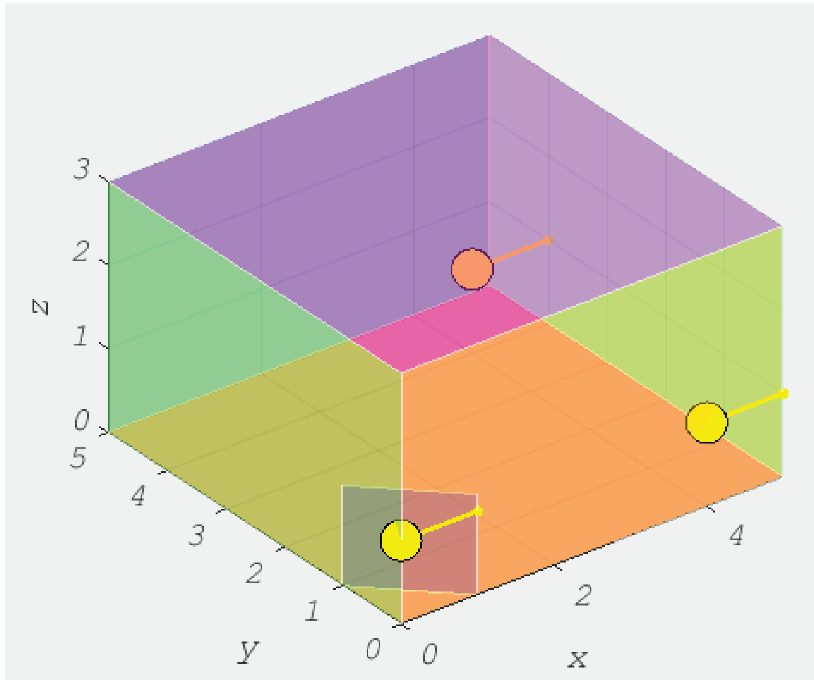


Figure 4.15. NLOS condition simulated with respect to B1

- **Test 5, 6, 7 :** Tests 2, 3, 4 were repeated with the obstacles placed at twice the distance between obstacle and beacons, when compared to Test 2, 3, 4. Height of the obstacle (1.2 m) is higher than the robot (as shown in Figure 4.16).
  Test 8: Obstacles of height 1m placed in front of B_1 and B_2.
- **Test 9:** Obstacles of height 1m front of B_1 and B_3.
- **Test 10:** Obstacles of height 1m placed in front of B_2 and B_3 as shown in Figure 4.17.

The generated time of flight measurements using Locusim were fed into the two stage ANN-LEU designed using Neural Network Toolbox in MATLAB. Based on the time of flight measurements, the ANN-LEU determines the target node positions and also outputs information on whether the estimated position is valid. If (x, y) is the actual target position and (X_{s1}, Y_{s1}) is the estimated position by ANN-LEU, then the error in position estimation is determined as

$$E = \sqrt{(x - X_{s1})^2 + (y - Y_{s1})^2} \tag{4.14}$$

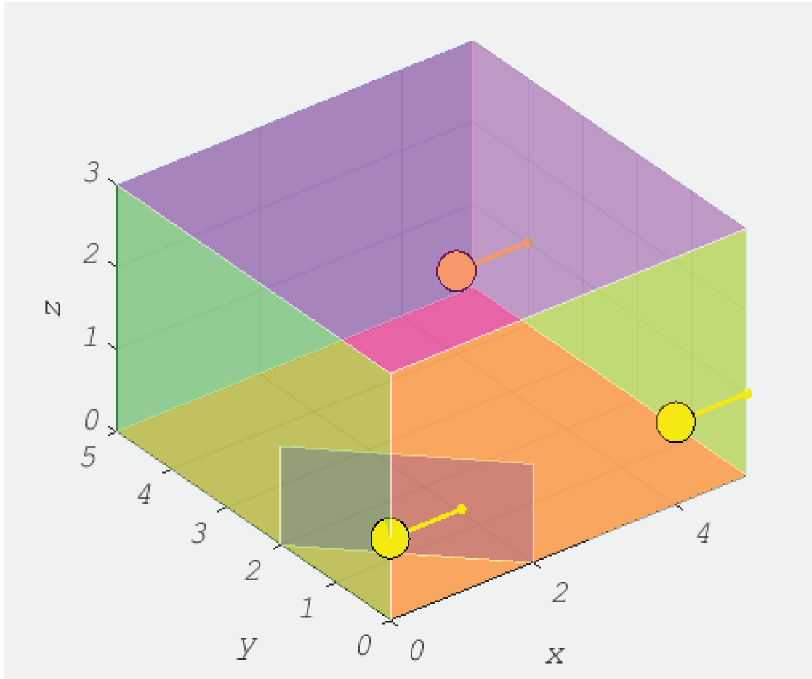


Figure 4.16. NLOS condition simulated with respect to B1- Test 5

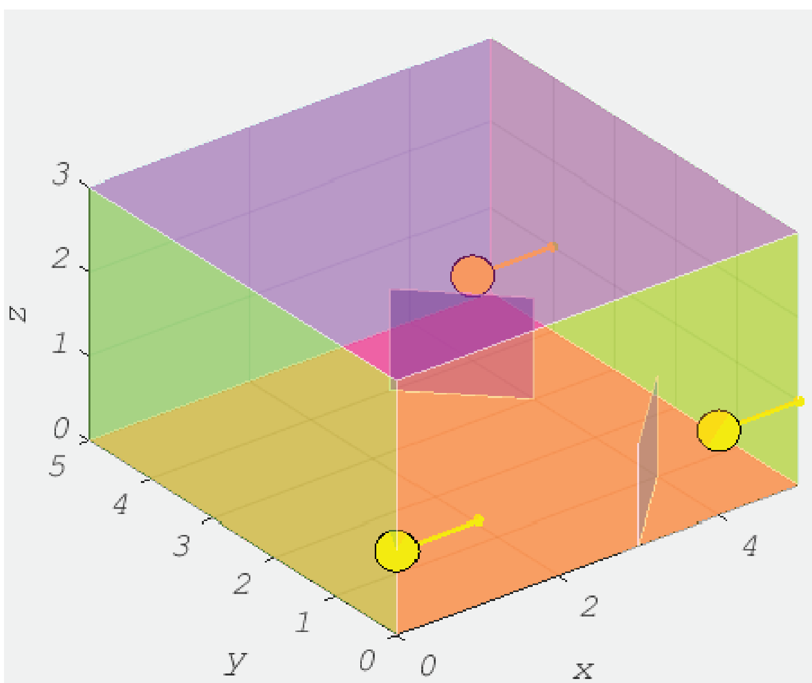


Figure 4.17. NLOS condition simulated with respect to B2 and B3

The Mean avearge error (MAE) for ‘n’ positions detected can be obtained as

$$MAE = \frac{\sum_{i=1}^{n}(E_i)}{n} \tag{4.15}$$

The Root Mean Squared Error (RMSE) is defined as

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(E_i)^2}{n}} \tag{4.16}$$

RMSE and MAE are used as metrics for performance evaluation of ANN-LEU. The following observations and conclusions were drawn from the different tests.

Performance Analysis of Test 1 : Other than for the two target nodes placed at (3.66, 3.99) and (0.15, 0.18), LOS condition was detected correctly for other 68 target node positions. For the above mentioned target node positions, based on the time of flight measurements, the target node position was estimated by ANN-LEU to be outside the boundary of 4m x 4m and hence the estimated position was considered as invalid by the ANN-LEU. The estimated and actual target position for the nodes is shown in Figure 4.18. The histogram representing the error distribution is given in Figure 4.19. Iteration 1 through the ILB block for four representative target node positions is as shown in Table 4.4 (other three ILB iterations are not shown as the acceptance criteria is not met for the other 3 iterations). The acceptance criteria is met only in the first iteration and hence after 4 iterations through the ILB, the estimated position is detected as valid. The performance metrics based on the 68 target nodes, whose location estimation was detected as valid by the ANN-LEU are as follows

- **Mean Average Error (MAE) = 11.44 cm**.
- **Root Mean Square Error (RMSE) = 11.53 cm**.
- **For an Accuracy of 20 cm, Precision (From Figure 4.19) = 92.64%**

Performance Analysis of Test 2 : For the deployment, other than for 2 of the target nodes, all other nodes are in NLOS with respect to B_1. For 6 target nodes which lie close to the 4m x 4m boundary, acceptance criteria was not met for any of the iterations. For the rest of the 64 nodes (2 in LOS and 62 in NLOS with respect to B_1), the performance metrics based on the nodes, whose location estimation was detected as valid by the ANN-LEU is

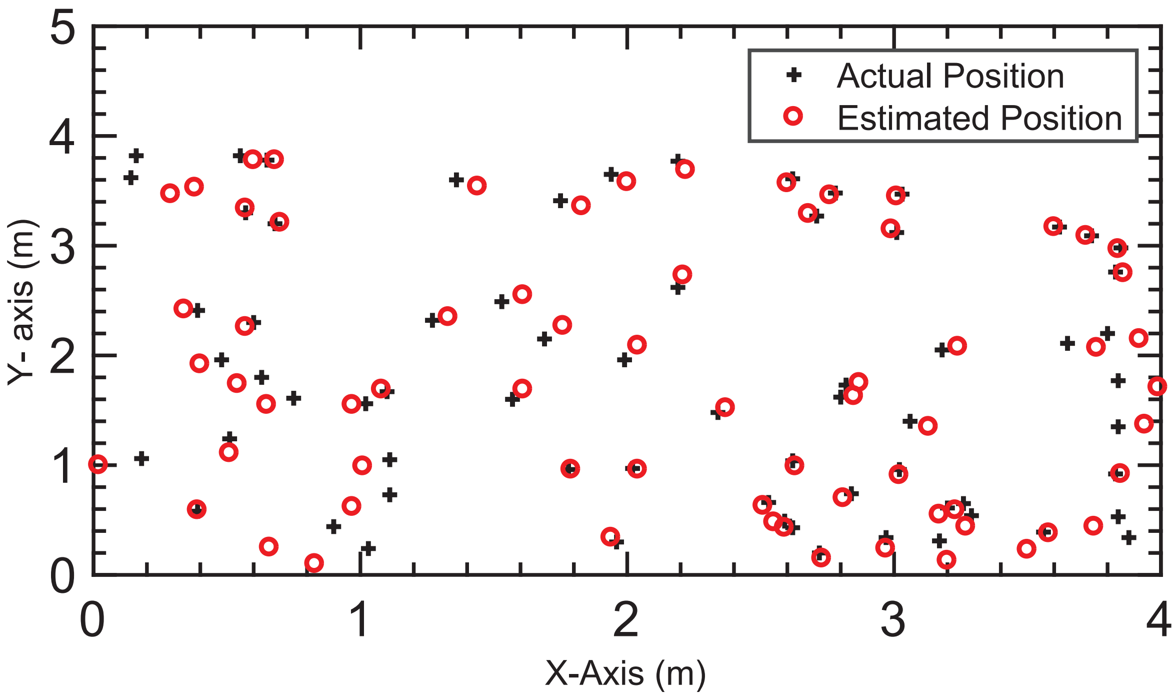


Figure 4.18. Actual Vs Estimated position of Target Nodes- Test 1

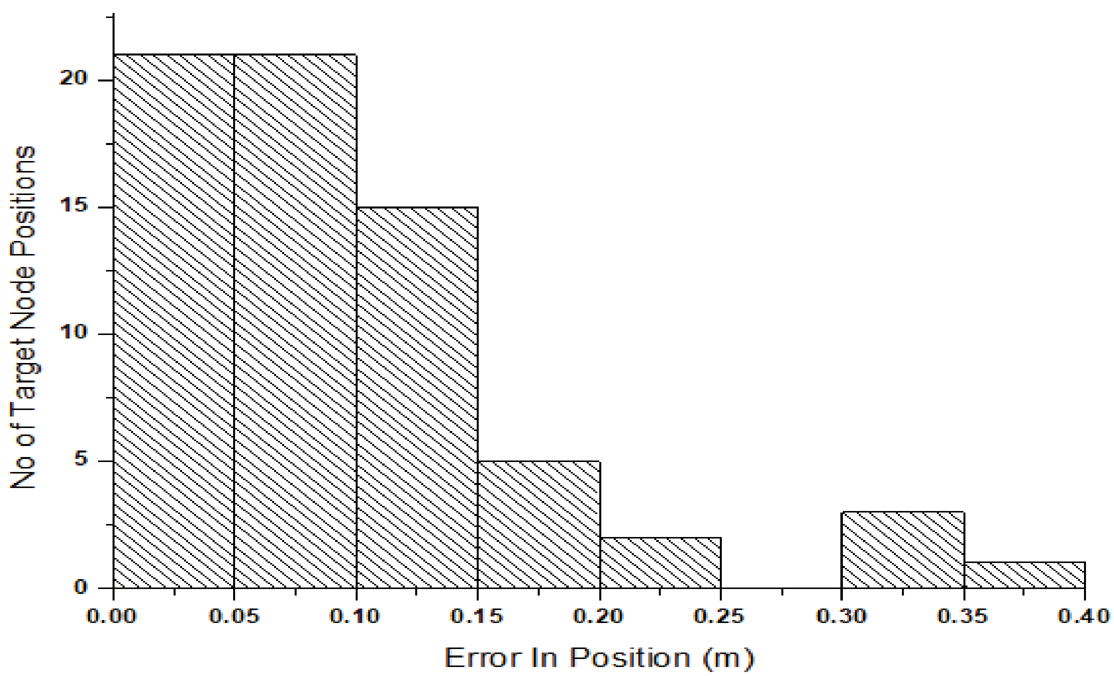


Figure 4.19. Histogram representing the error in estimated position- Test 1

Table 4.4. ILB block iteration for Test 1

Actual Target Position (x, y)	Iteration 1			
	(T_1, T_2, T_3)	(X_{S1}, Y_{S2})	(T_{S1}, T_{S2}, T_{S3})	$\lvert T_{sj} - T_k \rvert$ j∈ =1,2,3
(3.83, 2.76)	(13.69, 7.95, 3.5)	(3.86, 2.75)	(13.73, 7.92, 3.47)	(.03, .02, .02)
(1.11, 1.05)	(4.31, 8.86, 11.96)	(1.01, 0.99)	(4.01, 9.08, 12.27)	(.30, .21, .30)
(2.71, 3.27)	(12.30, 10.15, 4.18)	(2.68, 3.29)	(12.30, 10.24, 4.22)	(.00, .08, .03)
(0.7, 3.21)	(9.44, 13.375, 9.86)	(.68, 3.2)	(9.49, 13.37, 9.80)	(.04, .002, .05)

- **Mean Average Error (MAE) = 16.725 cm**.
- **Root Mean Square Error (RMSE) = 18.02 cm**.
- **% of target position detected valid, in the presence of NLOS for 1 timestamp= 57.1%**

Inference from Test 3 : When target node positions were estimated, for around 22% of nodes for which the acceptance criteria was met in the first iteration of ILB, however, the errror in position estimation for these nodes is more than 50cm. Generally if the acceptance criteria is met then the position error is less than 20 cm. Based on analysis, it was found that the acceptance criteria was met erroneously for certain target positions. For example, the Actual target position of the node is (2.59, .49) where as the estimated position is (0.59, 2.49). For this case, the position was detected as valid because when position is estimated with only time of flight measurements from B_1 and B_3, for the same time of flight measurement, target node can be at these two positions. (Arcs drawn from B_1 and B_3 may intersect at 2 different positions). Such a scenario will not occur when positon is estimated using time of flight measurements from B_2 and B_3 or B_1 and B_2 for the current deployment of beacon nodes. Arcs drawn from B_2 and B_3 or B_1 and B_2 cannot intersect at two points for the given deployment. Hence, it is concluded that target position estimation using B_1 and B_3 when timestamp T_2 is made '0' is unreliable and hence target node position estimation should not be attempted using measurements from B_1 and B_3 only. Performance metrics are given as follows.

- **Mean Average Error (MAE) = 53.7 cm**.
- **Root Mean Square Error (RMSE) = 71 cm**.
- **% of target position detected valid, in the presence of NLOS for 1 timestamp = 25.71%**

Performance Analysis of Test 4 : When atleast 1 node i.e B_3 was in NLOS condition, for 41 nodes, the NLOS was correctly detected and the position was calculated using other two values. The four iterations of the time of flight measurements through the ILB block for four representative target nodes is given in Table 4.5, Table 4.6 and Table 4.7. Performance results are as follows.

- **Mean Average Error (MAE) = 14.4 cm**.
- **Root Mean Square Error (RMSE) = 17.05 cm**.
- **% of target position detected valid, in the presence of NLOS for 1 timestamp = 58.57%**

Table 4.5. ILB block iteration for Test 4: Example 1

Actual Target Position	Iteration 1				
	(T_1, T_2, T_3)	(X_{S1}, X_{S2})	(T_{S1}, T_{S2}, T_{S3})	$\|T_{sj} - T_k\|$ j∈ =1,2,3	Position Valid
(0.6, 2.3) Iteration 1	(6.81, 11.89, 14.59)	(0.54, 1.67)	(4.98, 11.11, 12.07)	(1.83, 0.77, 2.51)	No
Iteration 2	(0, 11.89, 14.59)	(0.35, 1.24)	(3.57, 11.17, 13.27)	(X, 0.71, 1.31)	No
Iteration 3	(6.81, 0, 14.59)	(2.13, -0.71)	(6.15, 0.16, 6.81)	(0.25, X, 0.16)	No
Iteration 4	(6.81,11.89,0)	(0.51, 2.24)	(6.58, 11.99, 11.29)	(0.22, 0.10, X)	Yes

Table 4.6. ILB block iteration for Test 4 : Example 2

Actual Target Position	(T_1, T_2, T_3)	(X_{S1}, X_{S2})	(T_{S1}, T_{S2}, T_{S3})	$\|T_{sj} - T_k\|$ j∈ =1,2,3	Position Valid
(1.03, 0.24) Iteration 1	(2.93, 8.58, 18.14)	(0.61, 0.37)	(2.08, 9.80, 14.37)	(0.85, 1.22, 3.76)	No
Iteration 2	(0, 8.58, 18.14)	(0.56, -1.14)	(1.20, 6.67, 16.58)	(X, 1.91, 1.55)	No
Iteration 3	(2.93, 0, 18.14)	(1.84, -2.42)	(6.25, 4.27, 19.37)	(3.32, X, 1.23)	No
Iteration 4	(2.93, 8.58, 0)	(0.94, 0.24)	(2.72, 8.84, 14.10)	(0.22, 0.10, X)	Yes

Inference from Test 5: Performance results are as follows.

- **Mean Average Error (MAE) = 17.74 cm**.
- **Root Mean Square Error (RMSE) = 24.81 cm**.
- **% target position detected valid, in the presence of 1 NLOS condition= 66.12%**

Table 4.7. ILB block iteration for Test 4 : Example 3

Actual Target Position	(T_1, T_2, T_3)	(X_{S1}, X_{S2})	(T_{S1}, T_{S2}, T_{S3})	$\lvert T_{sj} - T_k \rvert$ j∈ =1,2,3	Position Valid
(2.53, 0.66) Iteration 1	(7.51, 4.56, 13.97)	(2.87, 0.69)	(8.48, 3.69, 10.09)	(0.97, 0.86, 3.88)	No
Iteration 2	(0, 4.56, 13.97)	(2.06, -0.2)	(5.96, 5.57, 13.39)	(X, 1.01, 0.58)	No
Iteration 3	(7.51, 0, 13.97)	(2.2, -0.4)	(6.49, 5.26, 13.77)	(1.01, X, 0.201)	No
Iteration 4	(7.51, 4.56, 0)	(2.5, .54)	(7.31, 4.47, 10.90)	(0.19, 0.08 , X)	Yes

Inference from Test 6: Performance evaluation of Test 6 is not presented here because as mentioned in Test 3 when target positions are calculated only based on B_1 and B_3 there will be false detection of position, as arcs drawn from the beacons can intersect at two points within field of deployment.
Inference from Test 7:

- **Mean Average Error (MAE) = 12.03 cm**.
- **Root Mean Square Error (RMSE) = 15.01 cm**.
- **% target position detected valid, in the presence of 1 NLOS condition= 85.71%**

Inference from 8, 9, 10: In these tests, among the nodes which are in NLOS conditions with respect to two beacons, for 100% measurements NLOS was detected at iteration 1. During Test 8, for fourteen nodes LOS was detected incorrectly. During Test 9, for two nodes LOS was detected incorrectly and during Test 10, for one node LOS was detected incorrectly across all four iterations through ILB.
NLOS detection accuracy = 91.9%
It was be observed that incorrect detection of LOS is predominant when B_1 and B_2 are in NLOS. As discussed in Test 3, arcs drawn from B1 and B3 can intersect at two different points in the zone of deployment leading to incorrect detection. To avoid this it is desired that the three beacons are deployed in such a way that the arcs drawn from the two beacons will not intersect at two different points within the coverage area.
The proposed system was also tested with the target nodes kept at a height of .8m and the beacon nodes kept at a height of 1m. The training of the ANN-LEU was performed again under LOS

conditions for the new deployment. On testing of ANN-LEU, the MAE error was estimated as 15.6cm and RMSE error was 19.2 cm for all 70 target positions (100% LOS detection) in perfect LOS conditions. In an SRS system with large number of robots it is desired that the beacons are kept at a certain height above the target nodes so that presence of other robots will not lead to NLOS conditions in time of flight measurements.

From the analysis presented above, it can concluded that the proposed ANN-LEU is robust and can provide localization within an accuracy of few tenths of centimetres, with lesser number of beacon nodes compared to the other ultrasonic based ILS systems described in Table 2.3. Another unique characteristic of the proposed scheme is that the training of the ANN is required to be performed only under LOS conditions. Hence the system can be easily trained in different environments, enabling quick deployments.

4.5 Conclusions

In this chapter, a two-dimensional beacon based indoor localization scheme for robots in SRS and MRS was presented.

- An ultrasonic transmitter and receiver system was designed, implemented and tested. The transmitter and receiver system provides a range of approximately 8 meters when the target and beacon nodes are placed at the same height, oriented towards each other. With RF communication, ultrasound beacons and time offset compensation, an accurate method for recording the time of flight or time of arrival measurements between of target and beacon node was developed. The time offset compensation proposed in Chapter 3 is utilized for the instantaneous time synchronization between the target and beacon node. The maximum error reported in ToA estimations during repeated experimentations is 13μs under LOS conditions. For any given temperature of the range, 15°C-35°C, error of 10μs will lead to a maximum variation in distance measurement of only ≈0.2cm.

- Having demonstrated the proof of concept of recording accurate time of arrival measurements using the hardware, a novel artificial neural network based scheme for location estimation from the time of arrival measurements, which is suitable for localization under LOS and NLOS conditions was developed.

- A two stage Artificial Neural Network based Location Estimation Unit (ANN-LEU) was presented which utilizes the time of flight measurement from target nodes and three beacon nodes to provide the (x,y) location estimation of the target. The unique characteristics of the proposed system is that the system is required to be trained only for Line-of-Sight (LOS) conditions.

- An neural network architecture which can be implemented on low-cost hardware was proposed for the ANN based location estimation unit.

- For a detailed study of different NLOS conditions, Locusim simulator was utilized. The time of flight measurements required for training and testing of neural network was generated using Locusim simulator. The generated timestamps were utilized for analyzing the accuracy of the proposed neural network based location estimation scheme using simulation of the neural network. The proposed ANN-LEU architecture was simulated in MATLAB using Neural Network toolbox.

- From the performance analysis of ANN-LEU following conclusions are derived. With three beacon nodes in LOS, for the 70 target nodes randomly deployed in 4m x 4m, the MAE error in the position obtained was 11.44cm. For 92.64% of the nodes, the MAE error was restricted to 20cm and the RMSE error in position estimation was only 11.53cm.

- The ANN-LEU can reliably identify the presence of NLOS if any, in the time of flight measurements. If the beacon nodes are placed in such a way that, the arc drawn from the two beacons do not intersect at two locations within the area of coverage, then even with two beacons in LOS, the location of target node can be estimated in a reliable manner using the proposed scheme.

- The MAE error in position estimated during the performance analysis was restricted to lesser than 20cm for LOS, and also for the scenarios in which, one of the three beacon nodes are in NLOS (also when the arcs drawn from beacons do not intersect at two different points). This is a significant improvement in performance when compared to the performance of available indoor localization systems which provide an accuracy in the range of 1-2.5 meters under NLOS conditions utilizing 3-8 beacons as mentioned in Table 2.3.

- The ANN-LEU could detect NLOS between more than 1 beacon for with a precision of 91.9% (for 210 test inputs) and thus invalidating the incorrect position estimation if any. The performance can be improved further if it the beacon nodes are placed in such a way that arcs drawn from any two beacons will not intersect at two points within the area of coverage.
- The proposed system can also achieve simultaneous localization of multiple target nodes as is desired in a scalable network.
- Since the system needs to be trained only under LOS conditions, it ensures quick deployment of MRS or SRS in unknown locations.
- The ANN-LEU can be adapted for indoor localization systems which is based on ToA measurement of beacon signals (e.g. UWB based ILS).

From the comparison of the positioning accuracy with popular ILS schemes (as mentioned Table 2.3), it can be observed that the proposed ANN-LEU based localization scheme can offer better accuracy under both LOS and NLOS conditions with a lesser number of beacons. A neural network based localization is a promising solution for indoor localization and with more complex neural network architectures it may be possible to achieve better accuracy.

The proposed scheme can be utilized for demand based localization which is initiated by the target robot or for periodic localization initiated by the beacon nodes. For a scalable network, periodic, beacon initiated localization is prefered for simultaneous localization of robots in the vicinity of the beacon. However, if the localization is repeated at shorter intervals of time, the wireless network will be heavily utilized for localization. Hence, inorder to ensure better utilization of wireless bandwidth and also to improve energy efficiency of the system, it is desired that the robots have the ability to localize themselves at least for shorter durations without the assistance of beacons. This is covered in the next chapter.