Mitigating the Effect of Obstacles in Narrowband Ultrasonic Localization Systems

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***Abstract*—This paper develops a method for mitigating the negative effects of obstacles in narrowband, time division multiple access (TDMA), ultrasonic localization systems. The method builds upon the robust Bayesian classifier for ultrasonic localization (RoBCUL) algorithm which utilizes an iteratively reweighted least squares (IRLS) scheme. This algorithm has the advantage of low computational cost but loses performance in the presence of obstacles. The improved version of the RoBCUL algorithm presented in this paper uses a statistical test applied after each iteration of the regression, using a weighted residual vector calculated from the weight matrix and residual vector. The technique was tested using experimental data with its performance being quantified by its ability to correctly classify all the signals received during a single TDMA cycle. The extended version performed significantly better in all obstacle scenarios than the original, correctly classifying 100% of TDMA cycles in the scenarios with no obstacles, 97.6% with one obstacle, and 89.0% with two obstacles.**

Keywords— least squares methods, Bayes methods, position measurements, reflection, ultrasonic transducers

I. INTRODUCTION

Ultrasonic localization systems are an attractive choice in 3-D indoor positioning applications. The hardware required is readily available at low cost. In addition, the low propagation speed of the signals allows for precise time of flight measurement and high accuracy 3-D position estimation.

While the specific configuration of these systems can vary, all of them share the common trait of having ultrasonic transducers in various positions which transmit and receive signals between themselves. The received data is used, along with known information about the system, such as the position of fixed transducers, to calculate the 3-D position of a transducer in an unknown location [1].

Solid objects in the space between the various transducers can obstruct the line of sight (LOS) transmission of signals. Furthermore, such objects can cause non-line of sight (NLOS) interference by providing a source of signal reflection and diffraction. The combination of blocked LOS signals and the presence of NLOS signals presents a challenging situation to any localization algorithm.

Methods that can be applied to overcome these challenges in ultrasonic applications can be split into three main categories: broadband techniques, geometric techniques and techniques based upon robust least squares.

Broadband techniques, such as code division multiple access (CDMA), which labels transmitted signals with identifying codes, can be used to good effect in overcoming both NLOS interference and the effects of signal loss due to obstruction. Codes, such as Gold codes, can be embedded into ultrasonic signals using techniques such as direct sequence spread spectrum (DSSS) or binary phase shift keying (BPK). The use of such schemes limits CDMA to systems that can transmit and receive broadband signals, such as those described in [2]-[3].

While broadband techniques exhibit high performance, they require broadband transducers. Commercially available broadband transducers are more expensive, require higher driving voltages and are generally more fragile than piezo-electric narrowband transducers.

In [4] a geometrical approach is taken for testing pairs of received signals, utilising a triangle inequality to filter outliers. The triangle inequality states that if two measurements are taken from two fixed beacons to the same third node, the difference between the two measurements cannot be greater than the distance between the two beacons. While this approach is fast and simple to implement it has drawbacks that make it unsuitable and less robust than competing methods.

These drawbacks include coarse granularity, with [5] pointing out that this method can fail in certain geometrical situations. Another major drawback is a lack of outlier identification; the technique can detect that there are outliers but cannot specify which measurements are the outliers.

Robust least squares techniques use information generated during regression, such as residuals, to determine how well each of the measurements fits with the rest of the data. This information is then used to take corrective action in limiting the effect of these measurements on the result.

Least trimmed squares (LTS) and least median squares (LMS) perform multiple regressions upon different subsets of the entire set of recorded measurements. The subset with the lowest overall regression error can be considered free of NLOS interference. While this technique is robust, it is computationally expensive [6].

LTS and LMS techniques can use the Levenburg-Marquardt (LM) algorithm to generate estimated positions for the various subsets of recorded measurements. Tests can then be applied to the solutions generated from these subsets, such as speed of sound estimation, as used in [7], or a test based upon position dilution of precision and the time of flight measurement error variance, as used in [8].

In a previous paper [9] the authors presented the RoBCUL algorithm, a robust classifier using Bayesian probability and iteratively reweighted least squares. This technique exhibited excellent performance in identifying and rejecting reflected NLOS signals and did so with a substantial saving in computational cost over similar methods. However, there is a loss of performance when the line of sight paths between receiver-transmitter pairs are obstructed.

For practical applications, such as the one outlined in [10], where the possibility of blocked signals is highly likely, it is essential to overcome the negative effects this can cause. The best available methods for doing this are the LTS and LMS techniques. However, these methods are computationally expensive, and it was due to this that the RoBCUL algorithm was originally developed in [9]. Therefore, the authors' chosen method to overcome this problem is to improve the existing RoBCUL algorithm.

II. Improved RoBCUL Algorithm

This section will present an additional weighting step, shown in Fig. 1, for the RoBCUL algorithm that increases performance in situations with signal blockages. In [9] the terms block and frame were defined to refer to specific windows of the received signal timeseries.

A block is defined as the window of this timeseries from the sample at which one transmitter begins its transmission to the sample immediately before the next transmitter begins its transmission. A frame is defined as the window of the timeseries which contains all the blocks for a single TDMA cycle.

The RoBCUL algorithm calculates the probability of a signal being LOS using the signals amplitude and a pair of Gaussian probability density function for the amplitude of LOS and NLOS signals. These probability density functions can be generated from a small set of known LOS and NLOS signals collected from the system before it is used.

The classification itself uses an iteratively reweighted regression working on the signals received during a single frame. Starting from an initial guess of the coordinates, held in a vector of parameters $\mathbf{x} = [x,y,z]^T$, this regression uses the LM algorithm to calculate parameter updates. During each iteration a custom reweighting rule is implemented that changes the weights of each of the signals depending on the current residual of the signal and its previously calculated probability.

By iteratively reweighting each of the signals in this manner, the weights of LOS signals converge to a value of one (giving them the maximum possible influence over the value of the parameter estimate) and the weights of the NLOS signals converge to zero giving them no influence.

Any given block can contain a single, multiple or no NLOS signals, it can also either contain zero or one LOS signals. The existing algorithm exhibits excellent performance when there is one LOS signal in every block. However, it struggles if this condition is not met, as the algorithm always attempts to classify one signal in each block as LOS.

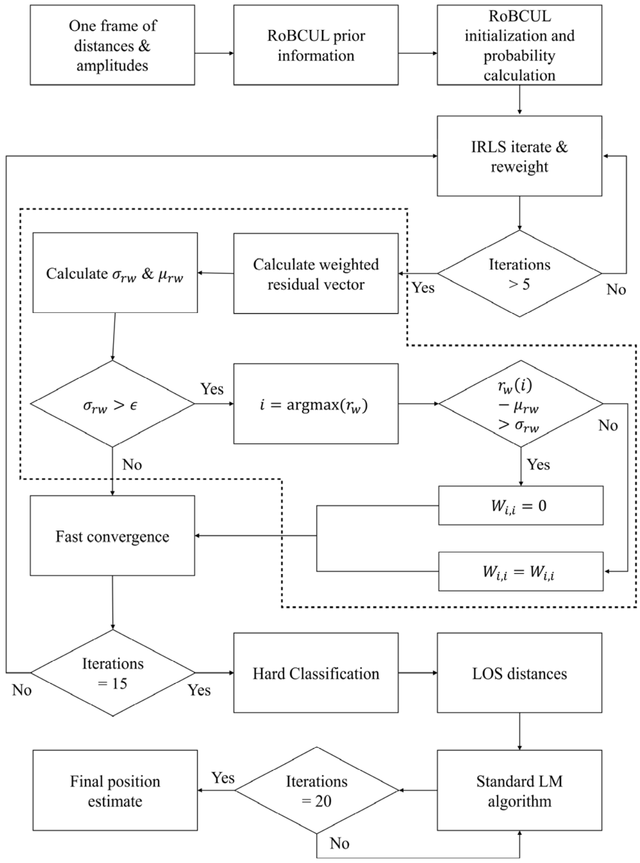


Fig.1 Flowchart showing the functioning of the algorithm extension within the original algorithm. The blocks within the dashed lines represent additions to the algorithm made in this paper.

A fault detection method has been developed for the RoBCUL algorithm as an extension of the existing weight update step, this step will allow for the above problem to be addressed by giving the algorithm more capability to decide if a signal should be left in or removed.

A. New Fault Detection & Exclusion Step

At the end of each iteration, each signal in the regression will have a weight and a residual. The current weight of each signal reflects how likely that signal is to be a LOS signal, while the signals residual reveals how well this signal fits with the current estimate of the position.

If the current estimate of the position is not too far from the true position then the LOS signals will have the lowest residuals of all the signals, while any NLOS signals will have higher residuals.

Weights in the range $0 \leq w \leq 1$ are assigned to each signal, with 0 being least likely and 1 being most likely. Therefore, correctly classified LOS signals will have a weight of near one and a residual near to zero, and a signal that is correctly classified as NLOS will have a weight near zero and a high value residual.

To detect faulty classifications, the weight matrix $\mathbf{W}$ can be multiplied by the absolute value of the residual vector $\mathbf{r}(\mathbf{x})$, resulting is a weighted-residual vector $\mathbf{r}_W$, with each of the elements of the vector corresponding, in order, to each of the signals. The absolute value is used because only the magnitude of weighted-residuals is important in detecting faulty classifications.

$$\mathbf{rw} = |\mathbf{Wr}(\mathbf{x})| \tag{1}$$

Since a false LOS signal is an NLOS signal with a weight near one, the element of **rw** corresponding to this signal will be large, whereas correctly classified signals will all have small weighted-residual values, either LOS signals with near unity weights and small residuals or NLOS signals with large residuals and near zero weights. Thus, false LOS signals will be easy to detect in **rw** due to the large magnitude of their weighted-residual.

False NLOS will be undetected by this method since these signals will have both small residuals and near zero weights, however such signals can be dealt with the existing reweighting procedure which will detect the low residual and assign a higher weight.

Once the weighted-residual vector has been calculated a method is needed to identify and exclude those signals which it identifies as incorrectly classified.

The standard deviation (σ_{rw}) and mean (μ_{rw}) of the weighted-residual vector are calculated. If all signals have been correctly classified both values should be small and consistent with the expected measurement error of the range measurements. The known value of the standard deviation of the measurement error is defined as ε. If the standard deviation of the absolute values of the weighted-residual vector is less than ε no corrective action will be taken, and it will be assumed that the signals have been correctly classified.

If $\sigma_{rw} > \varepsilon$ it will be assumed that there is at least one incorrect classification and corrective action will be taken. At each iteration the algorithm is given the chance to exclude a single signal, therefore the signal with the greatest weighted-residual will be considered. If this signal's weighted-residual is more than one standard deviation above the mean, then the signal will be rejected. The rejection is performed by setting the weight of the signal to zero.

If the maximum weighted-residual is the ith element in the weighted-residual vector, then:

$$\mathbf{W}_{i,i} = \begin{cases} 0 & \text{if} \quad \mathbf{r}_w(i) - \mu_{rw} > \sigma_{rw} \\ \mathbf{W}_{i,i} & \text{if} \quad \mathbf{r}_w(i) - \mu_{rw} \leq \sigma_{rw} \end{cases} \tag{2}$$

That is, the corresponding weight will be set to zero if the ith weighted-residual is more than one standard deviation above the mean and will be unchanged otherwise.

This process will be repeated during the iterations that follow until either the maximum number of iterations is reached or there are only three signals left with non-zero weights.

The value of ε is chosen as the standard deviation of the measurement error since if all the signals are correctly classified, then the values that will dominate the weighted-residual vector will be the residuals of the LOS signals. The error of these signals will therefore conform to the standard deviation of the measurement error for LOS signals. If there are NLOS signals classified as LOS signals then the standard deviation of the weighted-residual vector will be above that of the measurement error of LOS signals.

III. Experimental Testing

To test the proposed technique data was collected from a series of experiments. These experiments used eight transmitters held in two perpendicular planes and cylindrical pipes to act as obstacles.

A rig was designed and constructed for holding the transmitters and receivers in known locations during the experiment. The rig had two transmitter arrays, each of which held four transmitters, with each transmitter being positioned at the vertex of a square. These arrays were positioned so that one was parallel to the x axis and the other was parallel to the y axis, as can be seen in Fig. 2.

A receiver array was constructed and was placed upon a linear rail, allowing it to be moved though the space in front of the transmitters. The receiver array was positioned at a 45° angle to both transmitter arrays.

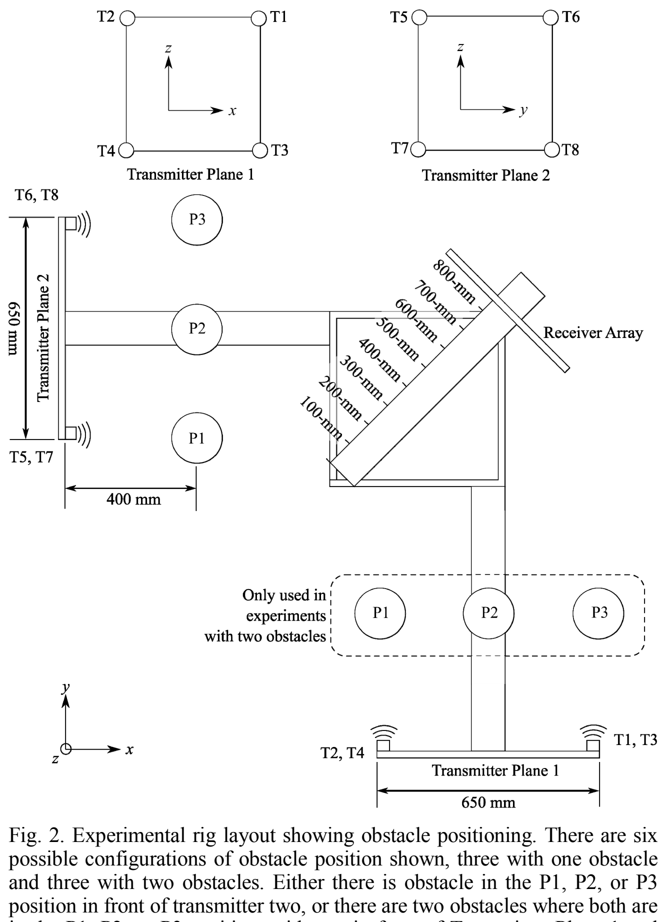


Fig. 2. Experimental rig layout showing obstacle positioning. There are six possible configurations of obstacle position shown, three with one obstacle and three with two obstacles. Either there is obstacle in the P1, P2, or P3 position in front of transmitter two, or there are two obstacles where both are in the P1, P2, or P3 position, with one in front of Transmitter Plane 1 and one in front of transmitter plane 2. At the top of the figure the layout of the individual transmitters is shown in each array's own plane.

The receiver array allowed for receivers to be held in any of 22 different positions within the plane of the array, and the linear rail mounting allowed the array to be positioned anywhere along an 800 mm track.

During the experiment intervals of 100 mm were used to position the receiver array. This allowed for seven different rail positions and a total of 176 possible receiver positions.

To investigate the effects of obstacles, cylindrical objects were placed in various positions between the transmitters and receivers. These cylinders, formed of hollow PVC ducting, were 150 mm in diameter and 1500 mm in height. The hard-plastic surface of the obstacles presents a highly acoustically reflective surface which further increases the environmental interference.

A full set of experiments was run with one and two obstacles as well as a full set run with no obstacles. During the experiments with obstacles, the obstacles were held in one of three positions (P1, P2, and P3) as shown in Fig. 2. All obstacles were placed 400 mm from the transmitter arrays as shown in Fig. 2.

In the experiments with one obstacle this pattern was followed placing the obstacle in front of only one transmitter plane. In the case with two obstacles, one obstacle was positioned in front of each of the transmitter arrays with the same positioning, i.e.: both obstacles in position one etc. Different combinations were not explored due to time constraints.

Due to only having four input amplifiers, it was only possible to record data from four of the 176 possible positions at a time.

1) The receivers were inserted into the array in the initial four positions. The rail was held at the 800mm mark, the furthest position from the transmitter arrays.

2) Data were recorded from all four receivers simultaneously in this position.

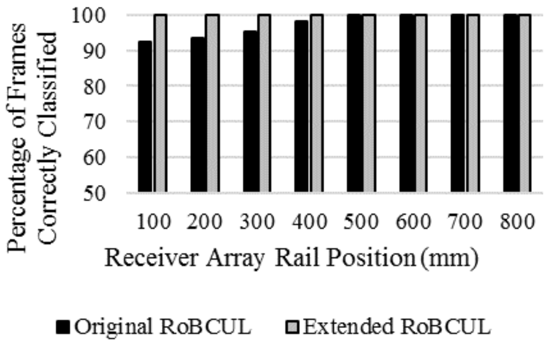
3) The receiver array was repositioned at the next 100mm interval mark and data were again recorded.

Steps 2 – 3 were repeated until the final rail position had been reached and its results recorded. The entire above process was repeated for each of the obstacle combination. The four receivers were repositioned in the array and the entire above process was repeated. This continued until data had been recorded from every position in the receiver array.

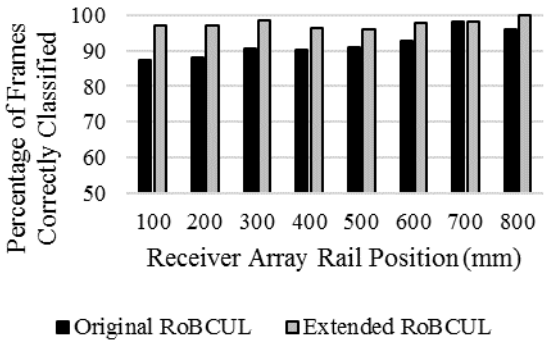
Each run consisted of sending 30 ultrasonic bursts from each transmitter. Each ultrasonic burst was twenty cycles with a frequency of 32.8 kHz. Input and output sampling was performed at 1 MHz. Each run was repeated three times.

IV. Experimental Results

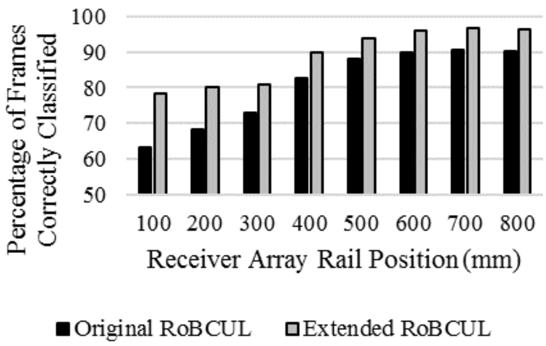
Results are presented here from testing the proposed algorithm on the data collected during the experiment. The classification results are shown in the bar charts in Fig. 3(a)-(c). These charts show the percentage of frames in which the algorithm was capable of correctly classifying all the signals, if even one signal in a frame is incorrectly classified then the frame is counted as a failure.. The charts are broken down by the position of the receiver array on its linear rail support. Table I presents the minimum, maximum and mean average values from each chart in Fig. 3.



(a)



(b)



(c)

Fig. 3. Classification results. (a) No obstacles. (b) One obstacle. (c) Two obstacles.

TABLE I. MINIMUM, MAXIMUM, AND MEAN CLASSIFICATION RESULTS FOR ALL EXPERIMENTS.

Algorithm	Number of Obstacles	Min	Max	Mean
Original	Zero	92.3	100	97.4
	One	87.2	98.1	91.8
	Two	63.0	90.7	80.8
Extended	Zero	100	100	100
	One	96.0	100	97.6
	Two	78.2	96.8	89.0

V. Discussion

The results shown in Fig. 3 demonstrate the performance of the proposed method. As would be expected, the best results are obtained in the experiments without obstacles and the worst are found in the experiments with two obstacles.

Table I shows the minimum, maximum and mean of these results. This shows that the extended algorithm, on average, correctly classified 2.6% more frames in the cases with no obstacles, 5.8% more frames with one obstacle, and shows the greatest increase in performance when two obstacles are present, with an 8.2% increase in the number of correctly classified frames.

The greatest increases in performance were in the experiments where the receiver array was in the 100-mm rail position. In this position, and with two obstacles, the use of the extended algorithm resulted in a 15.2% increase in the number of correctly classified frames. A trend can be seen in Fig. 2, of a deterioration in performance of both algorithms when the receiver array is in the sub-400-mm range.

This deterioration is due to the position and orientation of the transducers relative to one another, combined with the narrow beam angle of the transducers used in the experiments. Therefore, the loss of performance in these experiments was due to limitations of the hardware and experimental set up, rather than that of the algorithm. Despite these limitations the extended algorithm was capable of significantly increasing the performance of the localization algorithm in these cases.

When the receiver array was in the sub-400-mm positions, transmitters two, four, five and seven had a clear line of sight connection to the receiver plane. However, for the other four transmitters, the LOS path was at an average angle of 40° from the transmitters central axis, resulting in a -6 dB attenuation from the maximum sound pressure level. Similarly, once this signal reached the receiver, it did so at an angle of approximately 90° to the receiver central axis with a corresponding attenuation of -16 dB from the maximum sensitivity. Therefore, the LOS signals that were reaching the receiver from these positions were highly attenuated.

This attenuation causes failures, even in the cases where there are no obstacles to obstruct the signals. Due to the highly attenuated LOS signals the chance of only an NLOS signal being detected is much higher in the effected blocks. Due to the assumption of the original algorithm, that there would be one LOS signal in every block, this situation will cause the original RoBCUL algorithm to fail, as the single NLOS signal will be assumed to be LOS. However, with the additional step presented in this paper the extended algorithm can greatly diminish this effect in all cases.

VI. Conclusions

A method for mitigating the effects of obstructions in narrowband ultrasonic localization systems has developed and presented, this method extends the RoBCUL algorithm presented in [9].

The extended algorithm uses a weighted-residual vector, and a statistical test applied to the elements of that vector, at each iteration to detect NLOS signals that have been incorrectly classified as LOS. The extension not only gives the algorithm the ability to detect that there are faults, but also to determine which signals are faulty and to remove those signals.

The extended algorithm was tested on data collected during experiments which featured a number of obstacles in different positions. The extended algorithm performed better than the original RoBCUL algorithm in all scenarios, with 2.6% more frames correctly classified in the cases with no obstacles, 5.8% more frames with one obstacle, 8.2% more frames with two obstacles.

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