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ADAPTIVE DECISION TREE BASED LOS AND NLOS CLASSIFICATION

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ABSTRACT

Theperformanceof Underwater SensorNetworks (UWSNs) can be severely affectedbythedynamicsof underwater environment.Asurfacesinkisusuallydeployedatapre-specifiedlocation to maximize one or more performance metrics. The low sound speed in water makes propagation delay(PD)basedrangeestimationattractiveforunderwateracousticlocalization(UWL). Due to the long channel impulse response and the existence of reflectors, PD-based UWALsuffersfromsignificant degradation when PD measurements of non line-of-sight (NLOS) communication links are falsely identified as line-of-sight (LOS). In this project, Adaptive Decision Tree Classifier classifies LOS and NLOS links. It uses the decisions of multiple aspects of an object through a tapped delay line mechanism to impact the final decision of the current aspect. This system minimizes the error of the classifier. First, by comparing signal strength-based and PD-based range measurements, we identify object-related NLOS (ONLOS) links, where signals are reflected from objects with high reflection loss. In the second step, we use an algorithm to classify PD measurements into: LOS and sea-related NLOS (SNLOS), and to estimate the statistical parameters of each class. Both our simulation and sea trial results demonstrate a high detection rate of ONLOS links, and accurate classification of PD measurements into LOS and SNLOS.
***Keywords*— line-of-sight, non line-of-sight, Object-related NLOS (ONLOS) time-of-arrival classification, Underwater acoustic localization (UWAL),**

1. INTRODUCTION

Underwater acoustic communication networks (UWAN) are envisaged to fulfill the needs. The data derived from UWAN is typically interpreted .With reference to a node's location, for example, reporting an event occurrence, tracking a moving object or monitoring a region's physical conditions.How-ever,localization for underwater nodes is nontrivial. Since GPS signals do not propagate through water, localization of un localized nodes is often based on underwater acoustic communication and triangulation using asetofanchornodeswithknownlocations.Thisunderwaterac ousticlocalization(UWAL) typically employs propagation delay (PD) measurements for range estimation, i.e., time of arrival (TOA) or time difference of arrival (TDOA) of received signals. Existing UWAL schemes, for example, implicitly assume that PD measurements correspond to the line-of-sight (LOS) link between the transmitter and receiver. However, signals can arrive from non LOS (NLOS) communication links in several ways, as illustratedinFig.1.Forthenodepairs($u;a_2$)and($u;a_3$),sea surface and bottom reflections links (referred to as sea-related NLOS (SNLOS)) .Finally, between nodes u and a2, there is also an ONLOS link due to a ship. While it is expected that power attenuation in the LOS link is smaller than in NLOS links, it is common that the LOS signal is not the strongest. The underwater acoustic channel (UWAC) consists of groups of NLOS links with small path delay, but significant phase differences, often resulting in negative superposition with LOS and NLOS links are smaller than the system resolution for path separation) as well as positive superposition between NLOS links. For example, using basic trilateration, the localization errorgrowsquadratic ally with ranging offset, and azeromeanGaussian distributed offset with a standard deviation of only 2 msec would cause an average error of 6 merror One of the greatest challenges in communicating through the UWAC is the permanent motion of nodes at sea. This is because of mobility of nodes, such as for autonomous underwater vehicles (AUV), but also due to ocean currents. The continuous motion changes both the distance between transmitter and receiver and the channel impulse response of a communication link, including shifts in the arrival times and energy of signals received through different propagation paths. The proposed classification can improve the accuracy of UWAL by rejecting or correcting NLOS-related PD measurements, or by using them to bound range estimation. To implement our classification, we present two-step algorithm that classifies measurements into three classes: LOS, SNLOS, and ONLOS. We first identify ONLOS-related PD-measurements by comparing PD-based range estimations with range estimations obtained from received-signal- strength (RSS) measurements. The algorithm requires only a lower bound for RSS-based distance estimations a constrained adaptive decision tree classifier to classify the remaining PD measurements into LOS and SNLOS. Through a clustering of PD measurements, we mitigate changes in propagation delay due to mobility of nodes. The EMa lgorithmalsoestimatesthestatisticalparameters of both classes, which can be used to improve the accuracy of UWAL. First, our algorithm relies on significant power absorption due to reflection loss in ONLOS links, which are typical in the underwater environment. Second, we assume that the difference in propagation delay between signals traveling through SNLOS and LOS links which inacceptable in the UWAC due to the low sound speed in water (approximately 1,500 m/sec). Third, our algorithm is particularly beneficial in cases where NLOS paths are often mistaken for the LOS path, which occurs in UWAL, where the LOS path is frequently either not the strongest or nonexistent .Last ,the variance of PD measurements originating from SNLOS links is greater than that of measurements originating from LOS, which fits channels with long delay spread such as the UWAC. PD measurements for range estimation can be obtained1) From the symbols of a received data packet or 2)From multiple impulse-type signals transmitted in a short period of time. The PD is then estimated by setting a detection threshold to identify the arrival of the first path, a fixed threshold is set based on the channel noise level and a target false alarm probability. An adaptive threshold is used based on the energy level of the strongest path. In direct sequence spread spectrum (DSSS) signals, which have narrow autocorrelation, are transmitted to allow better separation of paths in the estimated channel response. The additional anchor nodes were used to resolve such ambiguities. a three-phase protocol is suggested for this problem. First, an ambiguity-free sub tree of nodes is determined. Then, localization based on triangulation is performed where the node is first assumed to be located in the center of a rectangular area. Finally, a refinement phase is performed using a Kalman filter to mitigate noise arising from ranging. For example, when there are insufficient anchor nodes or when the location of anchor nodes is almost collinear. The problem of localization when all measurements are obtained from NLOS links where the relationship between anchor node distances and NLOS factor is used to improve localization. The protocols are only applicable when a large number of anchor nodes are available. NLOS factor (i.e., the difference between the arrival times of the NLOS and LOS-based signals) is estimated using a maximum likelihood estimator based on an attenuation model, and NLOS-based measurements are incorporated after a factor correction instead of being rejected. However, to the best of our knowledge, no prior work considered a machine learning approach for NLOS and LOS classification of multiple PD measurements.

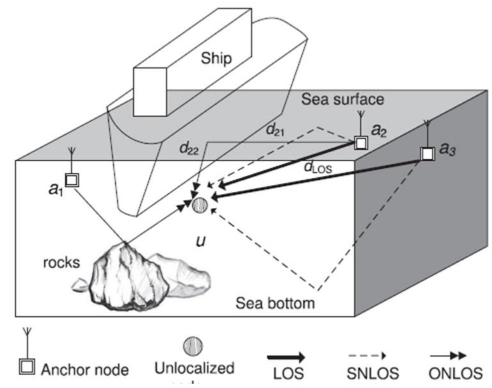

Fig. 1. Illustration of various types of communication links: LOS, SNLOS,
and ONLOS links.

II SYSTEM SETUP AND ASSUMPTIONS

From fig .1 The system comprises one or more transmitter-receiver pairs (u,aj), exchanging a single communication packet of N symbols or impulse signals, from which a vector $X = [x , \ldots , x]$ of PD measurements X , and corresponding measured time t is obtained using detectors

$$TL \quad (d \quad)$$

$$= TL \quad d \quad ,$$

$$+ TL \quad d \quad , \quad + RL$$

$$x = x \quad + n$$

Where x LOS is the PD in the LOS link, and ni is zero-mean (for LOS links) or nonzero-mean (for SNLOS or ONLOS links) measurement noise. Let dLOS denote the distance corresponding to x LOS, i.e.,dLOS = x LOS c. For the purpose of obtaining RSS-based range measurements, In this paper, we focus on transmission over short range(on the order of a few km), for which refraction of acoustic waves is negligible and propagation delay in the LOS link is shorter than in the NLOS links. For each measurement x , a PD-based estimate, d , is obtained by multiplying xi with an assumed propagation speed, c. In addition, based on an attenuation model for an

LOS link. we obtain RSS-based range estimates, d , $i = 1, \ldots, N$ from the received signals.

A .RSS-BASED RANGE MEASUREMENTS

Let d denote the distance corresponding to X i.e., $d = X$. C.

$$\mathrm{TL}_{\mathrm{LOS}}(d_{\mathrm{LOS}}) = \mathrm{PL}(d_{\mathrm{LOS}}) + \mathrm{AL}(d_{\mathrm{LOS}}) + \epsilon,$$

Where $\mathrm{PL}(d\ ) = \gamma \log\ (d\ )$ is the propagation loss, $\mathrm{AL}(d\ ) = \alpha$ —— is the absorption loss, γ and α are the propagation and absorption coefficients, respectively, and $\in$ is the model noise assumed to be Gaussian distributed with zero mean and variance φ. Considering the simplicity of the model, we do not directly estimate d but rather estimate a lower bound d , for which we apply upper bounds γ and α according to the expected underwater environment.

Foran ONLOS link with distance, $d = d + d$ where d and d are the distance from source to reflector and from reflector to receiver, respectively, we assume that the power attenuation in logarithmic scale is given by Burdic[27]

$$\mathrm{TL}\ (d\ ) = \mathrm{TL}\ \ d + \mathrm{TL}\ \ d + \mathrm{RL}$$

Where RL is the reflection loss of the reflecting object, whose value depends on the material and structure of the object and the carrier frequency of the transmitted signals. Since RL is often large, and due to the differences between models (2) and (3) we further assume that

$$\mathrm{TL}\ (d\ ) \gg \mathrm{TL}\ (d\ )$$

B .PDF FOR PD MEASUREMENTS

Since we assume changes in X are bounded by a small transmitter-receiver motion during the time X is obtained, we can model the PDF of the noisy measurement xi as a mixture of M = 3 distributions, corresponding to LOS, SNLOS, and ONLOS links, such that (assuming independent measurement noise samples

$$P(X|\theta) = \pi_{\epsilon} \sum k\ p(x|\omega\ )$$

Where $\theta = (\omega, K, \ldots, \omega, K)$ are the parameters of the m^{h} distribution, and K $(\sum K = 1)$ is the a-priori probability of the m^{h} distribution.

Clearly, $P(X|\theta)$ depends on multipath and ambient noise in the UWAC, as well as on the detector used to estimate xi. While recent works used the Gaussian distribution for $P(X|\omega\ )$, since multipath and ambient noises are hard to model in the UWAC, we take a more general approach and model it according to the generalized Gaussian PDF, such that

$$P(X|\omega\ ) = \frac{}{\Gamma(\text{—})} e\ \left(\frac{| \quad |}{}\right)$$

The actual distribution of PD in the LOS and NLOS links, the use of parameter β gives our model a desired flexibility, with $\beta = 1, \beta = 2$, and $\beta \rightarrow \infty$ corresponding to Laplace, Gaussian, and uniform distribution, respectively. We assume that PD measurements of NLOS links increase the variance of the elements of X. Thus, if ς , ς ,and , ς are the respective variance of measurements related to the LOS, SNLOS, and ONLOS links, then we have, $\varsigma < \varsigma$, $m = 2,3$

Since, for the PDF (6),

$$\varsigma = (\sigma\ )\ \frac{\Gamma(\frac{3}{\beta})}{\Gamma(\frac{1}{\beta})}$$

and by (8), ς does not change much with β constraint (7) can be modified to

$$\sigma < \sigma\ , \ m=2,3$$

Furthermore, let TLIR be the assumed length of the UWAC impulse response, which is an upper bound on the time difference between the arrivals of the last and first paths.

$$\overline{\varsigma} < T\ , \ m = 1,2,3$$

Moreover, the propagation delay through the LOS link is almost always shorter than those for any NLOS link.

Hence, we have

$$v < v < v + T\ , m = 2,3$$

Clearly, the more separable PD measurements from LOS and NLOS links are (i.e., the propagation delay difference is larger), the better the classification will be. Since the channel impulse response is longer for deeper channels, classification accuracy is expected to improve with depth.

C. REMARK ON ALGORITHM STRUCTURE

A two-step approach to classify PD measurements into LOS, SNLOS, and ONLOS. First, assuming large attenuation in an ONLOS link, we compare PD-based and RSS-based range estimates to differentiate between ONLOS and non-ONLOS links. Then, assuming PDF (6) for PD measurements, we further classify non-ONLOS links into LOS and SNLOS links.

The reason for separating classification of ONLOS and SNLOS links is insufficient information about the distribution of the two link types. For example, delay in ONLOS links may be similar to or different from that of SNLOS links. In the former case, classification should be made for M= 2 states, while for the latter three states are required. Since a mismatch in determining the number of states may lead to improper classification, we rely on the expected high transmission loss in ONLOS links to first identify these links. Furthermore, a separate identification of ONLOS links can be used as a backup to our LOS/ NLOS classifier. That is, we can still identify the link as ONLOS even when the channel is fixed, and thus PD measurements originate from a single link-type. In the following sections, we describe our two-step approach for classifying PD measurements.

III. STEP ONE: IDENTIFYING ONLOS LINKS

We identify whether measurement $x \in X$ is ONLOS-related based on three basic steps as follows:

- Estimation of d : We first obtain the PD-based range estimation as $d = c.x$
- Estimation of d' : Next, assuming knowledge of the transmitted power level, we measure the RSS for the i^h received signal/symbol, and estimate d' ,replacing γ and α with upper bounds γ and α , respectively.
- Thresholding : Finally, we compare d with d' ,.If $d' > d$,then x is classified as ONLOS. Otherwise, it is determined as non-ONLOS.

The RSS-based range estimation, d' is obtained from an upper bound for an attenuation model (2), i.e., from applying an attenuation model for an LOS link to an ONLOS link. Since the latter is expected to have a much larger power attenuation than the used model, it followsthat d' would be much larger than d .Similarly, consider a non-ONLOS link (i.e., LOS or SNLOS).Here, since we use an upper bound for the attenuation model, we expect to be smaller than d .Next, we analyze the expected performance of the above ONLOS link identification algorithm in terms of 1) detection probability of non-ONLOS links,P
and 2) detection
probability of ONLOS links, P .
To this end, since explicit expression for dLOS cannot be obtained from, in the following, we use the upper bound d' such that,

$$(\quad ' \quad) = \text{——}$$

is a tight bound when the carrier frequency is low or when the transmission distance is small.

A .Classification Of Non-Onlos Links

For non-ONLOS links, we expect $d, \leq .d$ Thus, since by bound $p(d, \leq .d) \geq p(d, \leq .d)$, and substituting, we get

$$P \geq 1 - Q\left(\frac{(\gamma - \gamma)(d - \alpha\frac{d}{1000})}{\emptyset}\right)$$

where Q(x) is the Gaussian Q-function.

B .Classification of ONLOS Links

When the link is ONLOS, we expect $d' \geq d$. Then, substituting, and since $p(d, \leq .d)p(d, \leq .d)$, we get

$$P \quad Q\{(\gamma \log(d) - \gamma \log d, d, - \alpha\frac{d}{1000} - RL\}/\{\emptyset\})$$

Next, we classify non-ONLOS links into LOS and SNLOS links.

C. STEP 2: CLASSIFYING LOS AND SNLOS LINKS

After excluding ONLOS-related PD measurements in Step 1,the remaining elements of X , organized in the pruned vector X , are further classified into LOS (m= 1) and SNLOS (m = 2) links and their statistical distribution parameters,ω , are estimated. Before getting into the details of our LOS/SNLOS classifier, we first explain its basic idea.

IV.BASIC IDEA

The underlying idea of our approach is to utilize the expected variation in link type of PD measurements due to mobility of nodes at sea. After identifying ONLOS links, this variation means that our set includes PD measurements of different values and link types. This allows us to use a machine learning approach to classify the measurements into two classes, LOS and NLOS. For this purpose, we use the adaptive e decision tree classifier algorithm. While using Decision Tree Classifiers (DTC's) are used successfully in many diverse areas such
as radar signal classification, character recognition, remote sensing, medical diagnosis, expert systems, and speech recognition, to name only a few. Perhaps, the most important feature ofDTC's is their capability to break down a complex decision-making process into a collection of
simpler decisions, thus providing a solution which is often easier to interpret. EM to classify measurements samples

into distinct distributions is a common approach, here the distribution parameters should also satisfy constraints, where the two latter constraints introduce dependences between the parameters of the LOS and NLOS classes. Furthermore, we incorporate equivalence constraints to group measurements of similar values into clusters which elements are classed to the same link type, thereby mitigating shifts in the value of X due to nodes' mobility. As we show later on, this result in a non convex maximization of the log-likelihood functions. For this reason, we present a heuristic suboptimal algorithm .In the following, we start by formalizing the equivalence constraints, and formulating the log-likelihood function .Next, we formulate a constrained optimization problem to estimate the distribution parameters, and present our heuristic approach to efficiently solve it. Given this estimate, we calculate the posterior probability of each PD measurement belonging to the LOS and SNLOS class, and classify the elements of X accordingly. Finally, we use decision tree classifier to classify the accurate measurements.

A .Equivalence Constraints

In setting equivalence constraints, we assume that the identity and delay of the dominant channel path, used for PD detection, is constant within a given coherence time, T ,and that for a bandwidth B of the transmitted signal, system resolution is limited by $\Delta T = -$. PD measurements satisfying equivalence constraints are collected into vectors Λ ; l 1; ...;L, where L denotes the number of such equivalence sets. Each PD measurement is assigned to exactly one vector, i.e., Λ have distinct elements. To formalize this, we determine X (recall that measurement X corresponds to measurement time$t$) and$X$ being equivalent, denoted as $X \Leftrightarrow X$,if

$$|t - t| \leq T$$

$$|x - x| \leq \Delta T$$

To illustrate this, X , X let and X correspond to the same class (either LOS or NLOS), such that$X$, X and. X , X This process continues until no two vectors can be merged. As a result, we reduce the problem of classifying$X \in X$ into classifying Λ , which account for resolution limitations and node drifting.

B .Formalizing the Log-Likelihood Function

Let the random variable λ be the classifier of Λ , such that Λ if is associated with class m; $m \in \{1,2\}$, then $\lambda = m$ .Also $\lambda = [\lambda, \ldots, \lambda]$ Since elements in X are assumed independent,

$$\Pr(\lambda = m|\Lambda, \theta) = \frac{k \quad p(\Lambda|\omega)}{p(\Lambda|\theta)}$$

$$= \frac{k \quad \prod_{\Lambda} p(x|\omega)}{\sum \quad k \prod_{\Lambda} p(x|\omega)}$$

From this we can write the expectation of the log-likelihood function with respect to the conditional distribution λ of given X and the current estimate θ as

$$L(\theta|\theta) = E[\ln(\Pr(X, \lambda|\theta))|X, \theta]$$

$$= \quad \Pr(\lambda = m|\Lambda, \theta) \quad \ln p(x|\omega) \quad \Lambda$$

$$+ \quad \Pr(\lambda = m|\Lambda, \theta)\ln k$$

Then we calculate $\Pr(\lambda = m|\Lambda, \theta)$

$$\Pr \lambda = 1 \ \Lambda, \theta \quad > \Pr \lambda = 2 \ \Lambda, \theta$$

$$K = \frac{1}{L} \quad \Pr \lambda = m \ \Lambda, \theta \quad , \quad m = 1,2$$

C. Estimating the Distribution Parameters

ω and ω

To estimate ω , we consider only the first term on the right-hand side, which for the is given by

$$(\ , \ , \ ) = \quad = \quad \Lambda,$$

$$\in\Lambda$$

$$-\ln(2 \quad) - \quad \Gamma \ \frac{1}{} \ - \ \frac{| \ -}{}$$

We find ω by solving the following optimization problem

$$\omega, \omega = \operatorname{argmin}_{,,} - \quad f(v, \sigma, \beta)$$

$$\text{s.t:} v \leq v \leq v + T$$

The convexity of $f(v \;, \sigma \;, \beta \;)$ depends on β ,
$\sigma - \sigma \leq 0$

$$\sigma \quad \frac{\Gamma\ \frac{3}{\beta}}{\Gamma\ \frac{1}{\beta}} - T \quad \leq 0, m = 1,2$$

Next, we use an algorithm to obtain the initial estimation, θ whose accuracy affects the above refinement as well as the convergence rate of the EM algorithm.

D. Forming Initial Estimation

Our algorithm to estimate θ is based on identifying a single group Λ_*, whose elements belong to the LOS class with high probability, i.e.$Pr(\lambda_* = 1) \approx 1$. Then used as a starting point for the K-means clustering algorithm, resulting in an initial classification λ for Λ , $l = 1, \ldots, L$ to form two classified sets X , $m = 1,2$. the mean, variance, and kurtosis of the elements in vector$X$ denoted as $E[X \;]$, $Var[X \;]$ and $K[X \;]$ respectively, to estimate θ using the following ,
$\frac{| \;\; |}{| \;\; |} = k$, $E[X \;] = v$, $Var[X \;]$toestimate θ using the following properties for distribution (6):

$$= \frac{\Gamma\ \frac{3}{}}{\Gamma\ \frac{1}{}} \quad , \quad [\quad]$$

$$= \frac{\Gamma\ \frac{5}{}\ \Gamma\ \frac{1}{}}{\Gamma\ \frac{3}{}} - 3$$

We assume that $\sigma < \sigma$ there is a small difference between measurements of the LOS link, compared to those of SNLOS links. Then we use the attribute to identify group λ_* by filtering X and calculating the first derivative of the sorted filtered elements. Group λ_* corresponds to the smallest filtered derivative.

C. ADAPTIVE DECISION TREE CLASSIFR

The decision tree classifier is one of the possible approaches to multistage decision making; table look-up rules .The basic idea involved in any multistage approach is to break up a complex decision into a union of several simpler decisions, hoping the final solution obtained this way would resemble the intended desired solution.

From graph A graph G = (V, E) consists of a finite, non-empty set of nodes (or vertices) Vand a set of edges E. If the edges are ordered pairs (v,w) of vertices, then the graph is said to be directed. A directed graph with no cycles is called a directed acyclic graph. A directed (or rooted) tree is a directed acyclic graph satisfying the following properties:

There is exactly one node, called the root, which no edges enter. The root node contains all the class labels.
Every node except the root has exactly one entering edge.
There is a unique path from the root to each node
A node with no proper descendant is called a leaf (or a terminal). All other nodes (except the root) are called internal nodes .The depth of a node v in a tree is the length of the path from the root to v. The height of node v in a tree is the length of a largest path from v to a leaf. The height of a tree is the height of its root. The level of a node v in a tree is the height of the tree minus the depth of v. An ordered tree is a tree in which the sons of each node are ordered (normally
from left to right).

The possible drawbacks of DTC, on the other hand, are: when the number of classes
is large, can cause the number of terminals to be much larger than the number of actual classes and thus increase the search time and memory space requirements. Errors may accumulate from level to level in a large tree. Finally, there may be difficulties involved in designing an optimal DTC. The
performance of a DTC strongly depends on how well the tree is designed.

V. DESIGN OF A DECISION TREE CLASSIFIER

The main objectives of decision tree classifiers are: 1) to classify correctly as much of the training sample as possible; 2) generalize beyond the training sample so that unseen samples could be classified with as high of an accuracy as possible; 3) be easy to update as more training sample becomes available 4) and have as simple a structure as possible. When a Bayes point of view is pursued, the optimal tree design may be posed as the following optimization problem

$$\underset{,\ ,}{\text{Minimize}} \quad (\;,\; ,\;)$$

where Pe is the overall probability of error, T is a specific choice of the tree structure, F and d are the feature subsets and decision rules to be used at the internal nodes, respectively. The implication of the above constraint is that, with a limited training sample size, the accuracy of the estimates of class conditional densities may deteriorate as the number of features increases. This is also known as the Hughes phenomena But, if one is allowed to select different feature subsets for differentiating between different groups of classes (i.e., a tree structure), one may be able to obtain even smaller probabilities of error than those predicted by Bayes decision rule.

The above optimization problem can be solved in two steps

Step 1: for a given T and F, find d* = d*(T, F) such that
P (T, F, d* (T,F)) = min P (T, F, d)
d

Step 2: Find T* and F* such that
P (T*, F*, d* (T*, F*)) = min P (T, F, d*(T, F)) T, F
It should be noted here that no mention of time complexity or computation speed has been made so far.
Some of the common optimality criteria for tree design are: minimum error rate, min-max path length, minimum number of nodes in the tree, minimum expected path length, and maximum average mutual information gain. The optimal tree is constructed recursively through the application of various mathematical programming techniques such as dynamic programming with look ahead (or back) capabilities to approach global optimality. In top-down approaches, the design of a DTC reduces to the following three tasks:

- The selection of a node splitting rule.
- The decision as to which nodes are terminal.
- The assignment of each terminal node to a class label.

VI.PERFORMANCE ANALYSIS

Simulation setting includes a Monte-Carlo set of10,000 channel realizations, where two time-synchronized nodes, uniformly randomly placed into a square area of1 km, exchange packets. The setting includes two horizontal and two vertical obstacles of length 20 m, also uniformly randomly placed into the square area, such that a LOS always exists between the two nodes. In each simulation, we consider a packet of 200 symbols of duration Ts =10 msec and bandwidth B = 6 kHz transmitted at a propagation speed of c = 1500 m/sec. To model movement In the channel(dealt with by forming groups l), during packet reception he two nodes move away from each other at constant relative speed of 1 m/sec, and is considered as the LOS distance between the nodes when the 100th symbol arrives .For each channel realization and node positions, find the LOS distance between the two nodes,.Based on the position of nodes and obstacles, we identify ONLOS links as single reflections from obstacles and determine v_3 as the average delay of the found ONLOS links. We use TLIR = 0:1 sec and we randomize v_2 according to a uniform distribution between $v_1$and v_1 + TLIR. For the other distribution parameters v .Then determine v , m = 1, 2,3 as an integer between 1 and 6 with equal probability (i.e., G =6)and ,m v =1,2,3 uniformlydistributedbetween0and,
.Tosimulatechannel attenuation v = 15, v =1:5 dB/km (considering a carrier frequency of 15 kHz),and set ∈ to be zero-mean Gaussian with variance 5=dB2//_Pa@1m. The source power level of 100 dB//_Pa@1m and a zero-mean Gaussian ambient noise with power20 dB//_Pa@1m, such that the signal-to-noise ratio (SNR) at the output of the channel is high. To obtain the lower bound on RSS-based distance, i = 1, . . . ,200, the attenuation model is given as dB/km. In Fig. 2, The PD is then estimated by setting a detection threshold to identify the arrival of the first path. Localization based on triangulation is performed where the node is first assumed to be located in the center of a rectangular area. When the location of anchor nodes is almost collinear. TOA measurements from different signals considerable reduction in measurement errors. The empirical detection probabilities for ONLOS and non

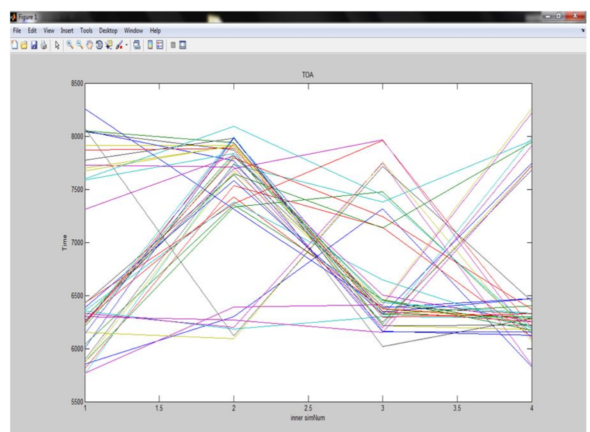

Fig 2 Time of arrival

In fig 3 To find LOS signal where two time-synchronized nodes, uniformly randomly placed into a square area of 1km, exchange packets. The setting includes two horizontal and two vertical obstacles of length 20 m, also uniformly randomly placed into the square area, such that a LOS always exists between the two nodes. For each channel realization and node positions, we find the LOS distance between the two nodes, and determine v = X

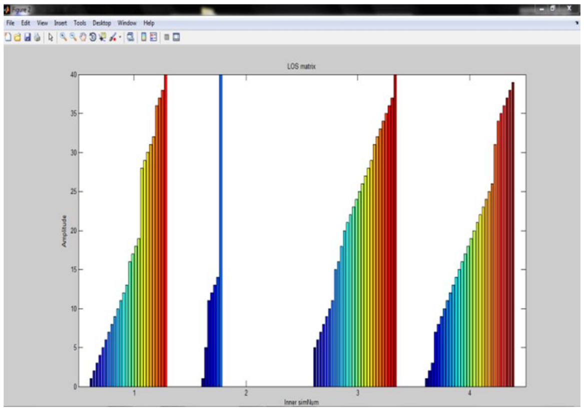

Fig 3 .LOS

In fig 4 To find Non line of sight signal the signal arrives from the reflection off a rock referred to as object-related NLOS that power attenuation in the LOS link is smaller than in NLOS links. From Fig.6, The empirical detection probabilities 4 for LOS (LOS (EM)) and SNLOS (SNLOS (EM)) links, the total detection probability (ALL (EM)), which is calculated as the rate of correct classification (of any link).Adaptive decision tree classifier, as well as the results for classification without prior identification of ONLOS links (No ONLOS ID), i.e., without the first step of our algorithm. Then latter, we consider two cases: 1) M = 2 and 2) M ¼=3, where in the second case ONLOS links are considered as a separate class . And observe the constrained decision tree classifier achieves a significant performance gain compared to the K-means algorithm used in the initialization process Fig

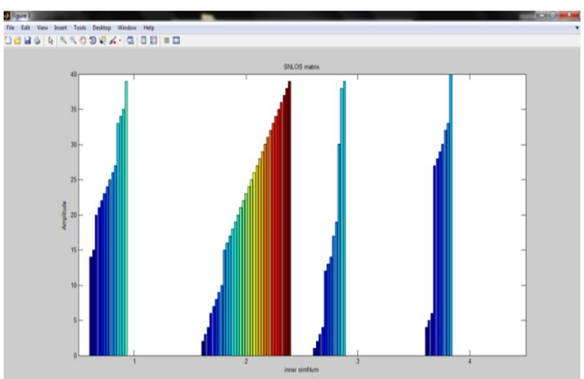

Fig 4. NLOS

Results show that for the former, the detection rate is more than 92 percent for both LOS and SNLOS. Observe the performance degradation for the first step for ONLOS identification is not performed. This degradation is more significant when ONLOS links are considered as SNLOS links, i.e., when M = 2.To find ONLOS and NON-ONLOS based on the position of nodes and obstacles, we identify ONLOS links as single reflections from obstacles and determine the average delay of the ONLOS links. ONLOS link identification are based on 1) detection probability of non-ONLOS links ONLOS link sand 2) detection probability of ONLOS links.In Fig. 7, we show the empirical complimentary

First, limit the number of features to be used at each stage. Secondly, for the sake of accuracy, specify tolerable error probabilities at each stage. Obviously the choice of linear classifiers and a binary tree structure is made to decrease computational complexity and time and thus to increase the speed.

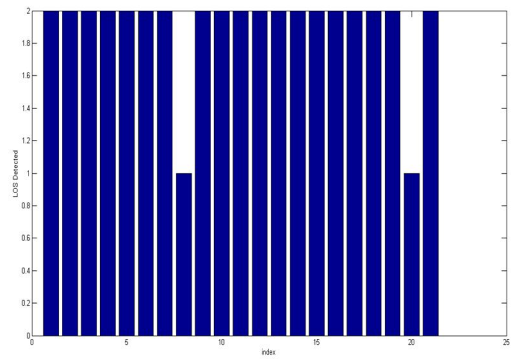

Fig 5. LOS Detected

The Outlier method outperforms the naïve approaches of using the average or minimum value of X, where the latter performs extremely poorly for large values For example, the proposed classifier achieves7 m in 90 percent of the cases, compared to 11.2 m when using the Outlier method, and the results are close to the HCRB.

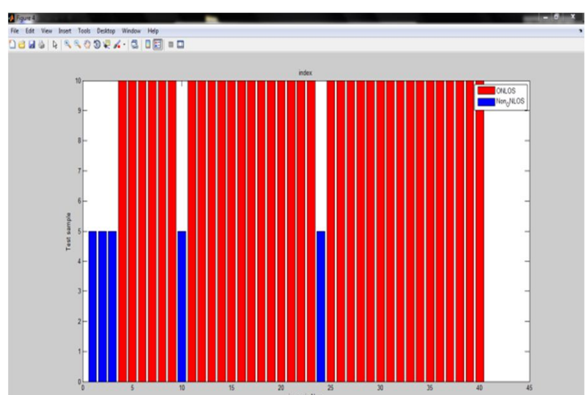

Fig 5. Classification results: (a) d

b)d

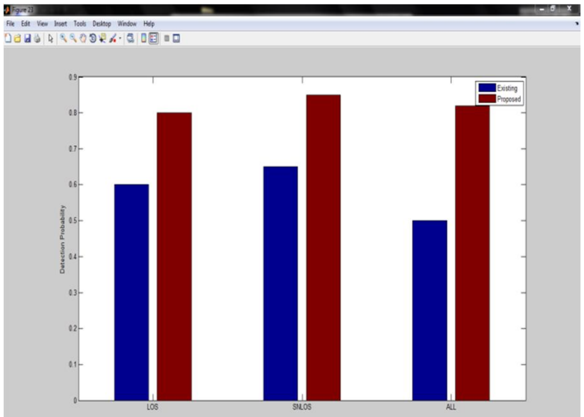

Fig.6Empiricaldetection probabilities of LOS and SNLOS

Such an improvement immediately translates into better localization performance as PD estimation errors significantly decrease. Due to cost decreases the tree structure get increased. Since even for moderately small numbers of features and classes, the number of possible trees is astronomically large, they suggested two restrictions to reduce the size of the search space.

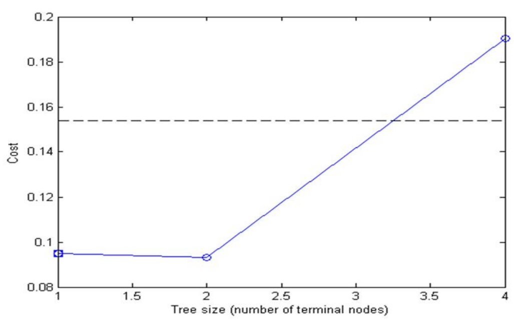

Fig. 7. Cost is minimum

Again, using a distance measure, such as Bhattacharyya distance, classes at each node are divided into two groups. Then, using an iterative procedure with an initial guess, a classifier is found that provides minimum probability of error.

VI. CONCLUSION

In this project the variation of propagation delay Measurements due to continuous motion of nodes at sea and classify the former into three classes: line-of-sight, sea surface- or bottom-based reflections (SNLOS), and object based reflections (ONLOS). We presented a two-step classifier which first compares PD-based and received signal strength-based ranging to identify ONLOS links, and then, for non-ONLOS links, classifies PD measurements into LOS and SNLOS paths, using a adaptive decision tree classifier. We also offered a heuristic approach to efficiently maximize the log-likelihood function, and formalized the Crame´r-Rao Bound to validate the performance of our method using numerical evaluation. The simulation and sea trial results confirmed that our classifier can successfully distinguish between ONLOS and non-ONLOS links, and is able to accurately classify PD measurements into LOS and SNLOS paths

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