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Study on Target Collaborative Localization in Underwater Acoustic Sensor Networks

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Abstract: A collaborative target localization algorithm in Underwater Acoustic Sensor Networks (UASN) is proposed. Comparing with other present algorithms about target localization, the algorithm is particularly considered time synchronization with high transmitting delay and acoustic multi-path propagation channel for UASN. By the condition of using new protocol of time synchronization, the target location is estimated by maximum-likelihood methods based on the range difference of wave arrival (RDOA), as the statistic model between the measuring and actual location is founded considering signal envelop in underwater channel. Meanwhile, the proposed algorithm adopts the distributed-centralized computation methods which degrade the node transmitting energy in underwater sensor networks. The result of simulation has analyzed the performance of localization precision.

Key words: Target localization, underwater sensor networks, time synchronization, multipath, maximum-likelihood

INTRODUCTION

Target localization has been the key application in radar, sonar, navigation and acoustic tracking. For the past few decades, a wide variety of target localization techniques based on the geometry theory had been proposed. According to the length of baseline, all the localization algorithms are divided into three types, Ultra-Short-Baseline (USBL), Short-Baseline (SBL) and Long-Baseline (LBL) (Qihu, 2003). However, the present algorithms have some limitations for passive target localization in underwater. In the case of the above algorithms, SBL and USBL have poor precision preferred to LBL, however it is not expedient to deploy the sensors array in underwater because of LBL's large size. Moreover, the LBL is not used in passive target localization because the correlation radius is not enough and the interval of observation is shorter. Preparing for the above deficiency, it is necessary to find novel methods to resolve the problem of underwater passive target localization.

Underwater acoustic sensor networks are consisted by a variable number of sensors which can self-organizes with short-range communication and multi-hop routing in underwater. Underwater sensor networks will find many applications in oceanographic data collection, pollution monitoring, offshore exploration, disaster prevention, assisted navigation and tactical surveillance applications which have been attracting increasing interest research in recent years (Heidemann *et al*., 2006). In all above applications, collaborative target localization is essentially important one, so in recently the novel collaborating target localization based UASN attract more attentions of scholar in different country (Wang *et al*., 2008).

In terrestrial wireless sensor networks, there are many methods to localize target. Most localization methods depend on three types of measured variables to localize target: Time Delay of Arrival (TDOA)/Time of Arrival (TOA), Direction of Arrival (DOA) and Received Signal Strength (RSS). Sheng and Hu (2005) localized the target by measuring the transmitting signal energy through the receiving sensor in wireless sensor network. Vijayakumaran *et al*. (2007) proposed an algorithm based on binary-detection information through distributed sensor by maximum-likelihood. Guerriero *et al*. (2009) introduced a sequential procedure to detect a target with distributed sensor networks using scan statistics. Li and Zhang (2007) studied a distributed and accurate algorithm for location based on manifold learning algorithms in wireless sensor network. However, there was little reports for localization in underwater sensor networks because of the complicated sea environment. Shenli and Willett (2007) studied the submarine location problem in underwater sensor network, the location is estimated by the detection information of underwater sensor. The algorithm makes better performance for

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submarine location which is a begin for collaborative target in UASN. Wang *et al*. (2008) analyzed the underwater acoustic transmit characteristic and studied the underwater target localization methods by measuring transmitting signal energy through underwater sensor. Wang *et al*. (2010) studied the method to localize the underwater target by measuring the direction of arrival by different underwater node in UASN.

All the above mentioned, algorithms didn't consider the time synchronization in UASN. They all made the hypothesis that every node is automatic synchronization perfectly. Although they focused on the localization method, the synchronization of underwater node can't be neglected. The synchronization must affect the performance of localization as the reality is based on time synchronization in UASN. Meanwhile, considering the limits on the node energy, the underwater node has to have little compute consume to localize target and algorithms have to reduce the complex of localization by distributed computation, then increase the network working time.

Therefore, the analysis of localization based on time synchronization in UASN was proposed in this paper. Firstly the high precise of time synchronization for UASN was achieved by adopting new approaches to time synchronization, Secondly the localization algorithm for underwater target in UASN based on the time synchronization was proposed which derived the maximum-likelihood source localization by the equation of Range Difference (RD) which is measured by Time Difference of Arrival (TDOA). Furthermore, considering the processing of compute, the distributed-centralized computation methods were adopted which degraded the transmitting energy of underwater sensor networks and make it applicable in engineering.

Source localization in underwater sensor networks: The scenario of the underwater target localization based on UASN is shown in Fig. 1. These buoy nodes can locate their position and get standard time by GPS (Wu *et al*., 2011) which can be regarded as the reference nodes. We will choose one as a sink node. Other underwater nodes can relatively locate their positions by network protocols with the help of sink node. Meanwhile, the underwater nodes have the wireless acoustic communicating ability and can be synchronized by sink node. Each node takes hydrophone sensor array (Fig. 2) to have the measuring range ability. In the case of the network scenario, the received signal is processed by distributed nodes and RD is estimated by each node and then the sensor transmits the value to the sink (center processing node) node to localize the underwater target.

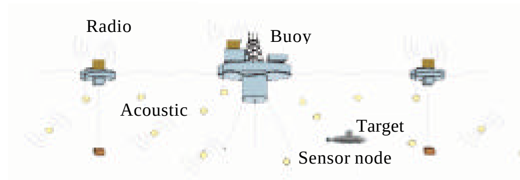

Fig. 1: Time synchronization in underwater sensor networks

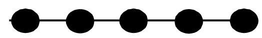

Fig. 2: Hydrophone array configuration of underwater sensor

Table 1: Comparison of transmit

Characteristic	Satellite	802.11RF	Underwater acoustic
Bit rate	155M b/s	11M b/s	20-50 kb/s
Typical BER	10^{-10}	10^{-5}	10^{-2}
Propagation delay	~120 ms	<1 µs	~300 ms
Distance	~42000 km	<3 km	<0.5 km

The proposed algorithm provides several advantages:

- The underwater target localization is achieved by multi-nodes of networks and has better precision comparing with traditional underwater target localization method
- Considering the reality, the target localization algorithm is based on the time synchronization and acoustic multi-path propagation channel in UASN
- The algorithm adopts the distribute-central joint compute method which degrades underwater node's computing and transmitting energy
- The node need not have more complicated computation, such as compute the DOA. Target location is estimated by RD

As following we will discuss the model and theory of the localization algorithm.

For the problem of the target localization in underwater sensor networks, the time synchronization of network is very import which will have more effect on localization. Several time synchronization protocols which maximize accuracy and energy conservation have been developed, including FTSP, TPSN and RBS. All of these assume nearly instantaneous wireless communication between sensor networks. But for underwater sensor networks where communication is primarily via acoustic telemetry (Wang *et al*., 2011), theses time synchronization protocols can not work well as the propagation speed is nearly five orders of magnitude slower than RF. Table 1 compares radio-based networks, satellites with short-range acoustic networks. Propagation delayis much higher comparing radio-based networks. New methods of time synchronization for UASN will be required to achieve better performance for target localization application, so it is designed assuming such high latency.

The high propagation delay of underwater acoustics is especially hazardous for time synchronization. However, NTP tolerates high delay, it does not consider energy consumption problem. UASN based time synchronization protocols must consider energy consumption but all current protocols are designed for RF-based networks, assuming nearly instantaneous and simultaneous reception such as RBS Elson *et al*. (2002) FTSP (Maroti *et al*., 2004) or ignore clock drift during synchronization such as TPSN (Ganeriwal *et al*., 2003), LTS (Greunen and Rabaey, 2003) which are not applicable to high latency networks because these methods do not consider propagation delay at all. Syed and Heidemann, 2006) demonstrated the existing protocols such as RBS, TPSN and FTSP do not work well for high latency links. The accuracy of time synchronization for TPSN will be degraded by increasing distance, or skew between nodes.

So we will realize target collaborative localization based on UASN, we must analyze and design better time synchronization algorithm for UASN. The simple way to introduce a new protocol is to identify the constraints and quantify the inaccuracies these constraints impose on current time synchronization protocols.

The key idea of the protocol for UASN is to split time synchronization into two stages. In the first stage, nodes estimate clock skew to a centralized time-base. In the second stage these nodes swap skew compensated synchronization messages to define the offset. The first stage is imperious to the propagation latency while the second stage explicitly handles propagation delay induced errors.

Time synchronization for UASN (TUPSN) has two phase protocols. The key idea is to first model the uncorrected clock of a underwater node as f_s (t) and its corrected time as $\hat{f}_s(t)$:

$$f_s(t) = a_s t + b_s$$

$$\hat{f}_s(t) = f_s(t) + \beta_s(t) \tag{1}$$

These are linear function of its skew a_s and offset b_s, where, t is the global reference time and β (t) is the correction factor calculated at t. Secondly each node in the broadcast range of a Beacon node models its clock skew. We define the Beacon nodes (buoy node) clock as the reference time base which can connect to an external time reference like the GPS or other buoy node. The Beacon node then sends out enough Beacon messages for skew estimation by reasonable linear regression. Thus, for N message M_t, we can using the following data points to linear regression:

$$(t_{B,i} - f_R(t_{B,i} + D_{B\to R}), f_R(t_{B,i} + D_{B\to R})) \tag{2}$$

where, D_{b-R} represents the unknown propagation delay between the Beacon node and the receiver node, f_R $(t_{B,i} + D_{b-R})$ is the assigning local time, $t_{B,i}$ is the timestamp from the Beacon messages. Each node is skew synchronized by performing linear regression by multi-beacon values.

In the second phase we correct for clock offsets. The existing protocols such as NTP and TPSN do time synchronization with a send-receiver two-way message exchange. We take this approach as well. But the protocol for UASN considers a skew-compensated two-way exchange. TUPSN's two-way exchange differences in that we correct for skew when computing the clock offset. When the receiver obtains enough beacons to estimate the skew it sends a synchronization request message with $T_I = f'_R(T_I)$, the skew-corrected local timestamp. The Beacon node records its local version of this $f_B = (T_I + D_{R-B})$ and returns its value to the receiver in a synchronization reply message time-stamped at T_3 which computes a skew-corrected receive time $f'_R(T_3 + B\text{-}R)$. Finally the receiver can compute its clock offset:

$$\beta_R = [(f_B(f'_R(T_1) + D_{R\to B}) - f'_R(T_1)) - (f'_R(T_3 + D_{R\to B}) - T_3)] / 2 \tag{3}$$

When this exchange completes, the underwater nodes are able to factor out the error than occurs because of skew and get the exact offset. So the high precision protocol for synchronization in UASN is very useful to the problem of target localization allowing for the more location performance. The simulation of the above protocol of time synchronization for UASN (TPSUN) is done, whose packed level is designed for high latency in underwater environment. Meanwhile, we compare the protocol with the traditional TPSN, demonstrating that the TPSN's accuracy deteriorates at high latencies because it need not to model skew in its environment. In simulation result in Fig. 3, we evaluate error as a function of the distance between the underwater node receiver and the Beacon node. The simulation showed that in both protocols is linear with time but the slope of TPUSN is much less because of its modifiability which is very useful to target localization for UASN.

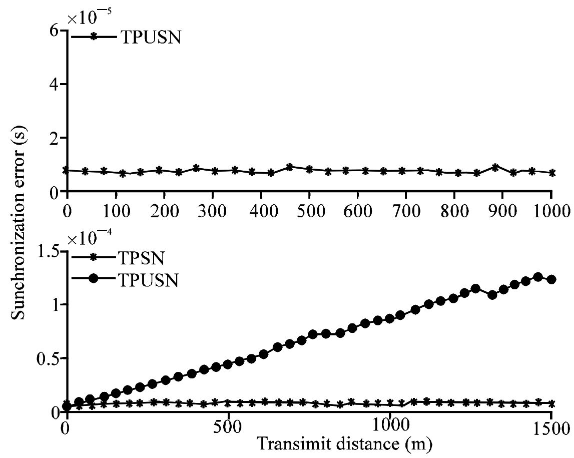

Fig. 3: Simulation of time synchronization error for UASN

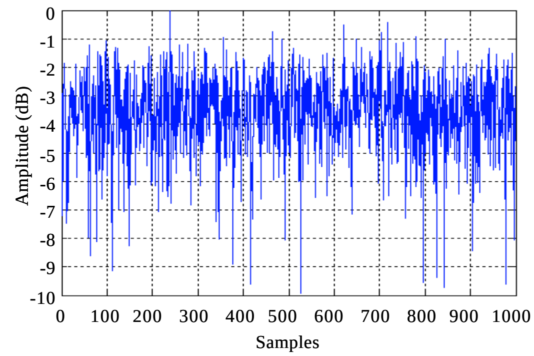

Fig. 4: Rician fading envelope for K = 6dB

Analysis on multiple paths of underwater acoustic channel: As the propagation medium is limited by the sea surface and the seabed, the signals transmitted undergo successive reflection at the interfaces. Variations in sound velocity within the medium may also deform the paths of sound waves. Due to these processes, a given signal can therefore propagate along several distinct paths. These multiple paths are typical of underwater acoustics and can be very penalizing. These paths will cause the signal fading. So, we must consider the effect on acoustics in order to improve performance of localization. The fading amplitudes can be modeled by a Rician or a Rayleigh distribution, depending on the presence or absence of specular signal component. In this paper, we model the underwater fading channel with Rician-distributed.

Let r_i represents the fading amplitude. The i-th time instant can be represented as:

$$r_i = \sqrt{(x_i + \beta)^2 + y_i^2}$$

where, β is the amplitude of the specular component and x_i, y_i are samples of zero-mean stationary Gaussian random processes each with variance σ^2_0. The ratio of specular to defuse energy defines the so-called Rician K-factor which is given by:

$$K = \beta^2 \big/ 2\sigma_1^2 \; .$$

The best-case and worst-case Rician fading channels associated with K-factors of $K = \infty$ and $K = 0$ are the Gaussian and Rayleigh channels with strong LOS and no LOS path, respectively. So, the Rayleigh fading channel can be considered as a special case of a Rician fading channel with K = 0. The Rician PDF is given by:

$$f_{Rice}(r) = \frac{r}{\sigma_0^2} \exp[-(r^2 + \beta^2) / 2\sigma_0^2] I_0[\frac{r\beta}{\sigma_0^2}], r \geq 0 \qquad (4)$$

where, I_0 [.] is the zero-order modified Bessel function of the first kind. Now, if there is no dominant propagation path, K = 0 and I_0 [.] = 1 yielding the worst case Rayleigh PDF. A typical Rician fading envelope is shown in Fig. 4, where the fading amplitudes are plotted in decibels which will cause the signal fading.

Localization model based on maximum-likelihood: Based on the above time synchronization and the model of underwater channel, the algorithm of localization will be proposed in the following. The localization algorithm has three phases. One is that underwater node measures the range between the node and source. The second is that the node transmits its range to sink node. The last is that the sink node establishes the statistic model between the target and the nodes based on measured Range Difference (RD) and sink node estimates the target position by maximum-likelihood method.

Time of Arrival (TOA) is usually used to estimate the range for collaborative target, however, the TOA is invalid in non-collaborative target as we can't exactly know the start time that signal transmit from source. TOA is not used to passive location. So, in this paper we will determine the range through triangle geometry based on the Δ_t (time difference of arrival which is proposed by array signal processing. In the following, we will derive the localization algorithm.

Let N denotes the number of the underwater nodes. The 3-D position vector for the i-th node is denoted by:

$$\vec{x}_i = [x_i \quad y_i \quad z_i]^T, \; i = 1, 2...N$$

where, we choose the sink node as the reference node and thus the position of the node is set the origin of the Cartesian system and it's position is $\vec{x}_1 = \vec{0}$. Vector

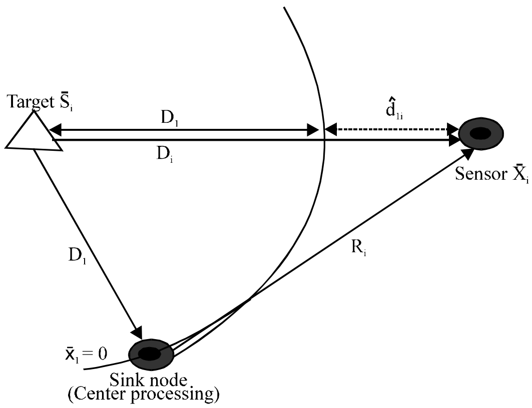

Fig. 5: Geometry configuration of target localization

$\bar{y} = [x \quad y \quad z]^T$ represents the underwater target location, then the distance between the target and node is denoted by:

$$D_i = \|\bar{x}_i - \bar{y}\| = \sqrt{(x_i - x)^2 + (y_i - y)^2 + (z_i - z)^2} \tag{5}$$

where, D_i represents the distance between the target and sink node. The pairs of Range Difference (RD) between the D_i (i = 2,3,....N) and D_i is represents d_{1i} by:

$$d_{1i} = D_i - D_1 \tag{6}$$

Similarly, the measured distance of D_i is represented by $D_i^{(m)}$ which is estimated through the hydrophone array using the triangle geometry by each node i, whose configuration is shown in Fig. 5. The measured RD is represented $d_i^{(m)}$ which is estimated by the node transmitting its measured $D_i^{(m)}$ to sink node by $d_i^{(m)}$. Let $\hat{d}_{1i} = \varepsilon_i - \varepsilon_1$, respectively represents the measure errors which are random variables, then the $D_i^{(m)}$ and $d_{1i}^{(m)}$ can be rewrite as:

$$d_{1i}^{(m)} = d_{1i} + \hat{d}_{1i} \; D_i^{(m)} = D_i + \varepsilon_i \, D_1^{(m)} = D_1 + \varepsilon_1 \tag{7}$$

where, $\varepsilon_1 \sim \mu(0, \sigma_0^2), \varepsilon_i \sim (0, \sigma_i^2)(i = 2, 3 \cdots N)$. $\hat{d}_{1i}$ can be derived from Eq. 6 and 7 as:

$$\hat{d}_{1i} = d_{1i}^{(m)} - d_{1i} = D_i^{(m)} - D_1^{(m)} - d_{1i} = D_i + \varepsilon_i - D_1 - \varepsilon_1 - d_{1i} \tag{8}$$

We substitutes Eq. 6 for the Eq. 8, the $\hat{d}_{1i}$ can be rewrote by:

$$\hat{d}_{1i} = \varepsilon_i - \varepsilon_1 \tag{9}$$

According to statistic theory and the Eq. 6 the variable $\hat{d}_{1i}$ is subject to normal distribution with $\hat{d}_{1i} \sim (0, \zeta_i^2)\,(i = 2, 3 \cdots N)$,

Where:

$$\zeta_i^2 = \mathrm{Var}(\hat{d}_{1i}) = E[(\hat{d}_{1i} - E(\hat{d}_{1i}))^2] = E[(\varepsilon_i - \varepsilon_1)^2] = \sigma_i^2 + \sigma_0^2 \tag{10}$$

Let us now define the following matrix notations:

$$\begin{aligned} H &= [\hat{d}_{12}, \hat{d}_{13}, \cdots, \hat{d}_{1N}]^T \\ K &= [d_{12}^{(m)}, d_{13}^{(m)}, \cdots, d_{1N}^{(m)}]^T \\ \Delta &= [d_{12}, d_{13}, \cdots, d_{1N}]^T \\ v_{mn}^2 &= \mathrm{Var}(\hat{d}_{1m}, \hat{d}_{1n}) = E[(\varepsilon_m - \varepsilon_1) \cdot (\varepsilon_n - \varepsilon_1)] \quad (m, n = 2, 3 \cdots N) \end{aligned} \tag{11}$$

where, H, K, Δ, respectively represents the vector value of $\hat{d}_{1i}$ and $d^{(m)}_{1i}$. We can deduce the variance of H from the above (11) as:

$$\begin{aligned} \Sigma &= \mathrm{Var}(H) = E[(H - E(H)) \cdot (H - E(H))^T] \\ &= E[H \cdot H^T] = \begin{vmatrix} v_{22}^2 & v_{23}^2 \cdots & v_{2N}^2 \\ v_{32}^2 & v_{33}^2 \cdots & v_{3N}^2 \\ \vdots \; \cdots & \ddots & \cdots \\ v_{N2}^2 & v_{N3}^2 \cdots & v_{NN}^2 \end{vmatrix} \end{aligned} \tag{12}$$

where, v^2_{mn} is covariance of the RD measured by the m-th and n-th node and $v^2_{mn} = \zeta^2_i$, (m = n = i). Σ is the covariance matrix of H. Considering the positions of nodes and target, we substitute (5) for the above equation and rewrite H as:

$$H = \begin{vmatrix} \hat{d}_{12} \\ \hat{d}_{13} \\ \vdots \\ \hat{d}_{1N} \end{vmatrix} = \begin{vmatrix} d_{12}^{(m)} - d_{12} \\ d_{13}^{(m)} - d_{13} \\ \vdots \\ d_{1N}^{(m)} - d_{1N} \end{vmatrix} = K - \begin{vmatrix} \|\bar{y} - \bar{x}_2\| - \|\bar{y} - \bar{x}_1\| \\ \|\bar{y} - \bar{x}_3\| - \|\bar{y} - \bar{x}_1\| \\ \vdots \\ \|\bar{y} - \bar{x}_N\| - \|\bar{y} - \bar{x}_1\| \end{vmatrix} \tag{13}$$

The likelihood function of K given $\vec{y}$ is:

$$f\,(K; \bar{y}) = \frac{1}{2\pi^{\frac{(N-1)}{2}} |\Delta|^{\frac{1}{2}}} e^{-\frac{1}{2}(K-\Delta)^T \Sigma^{-1}(K-\Delta)} \tag{14}$$

where, the symbol Σ is covariance matrix . We assumed the RD variance measured by sink node is σ^2_0, the one measured by other nodes is σ^2 and the RDs measured by nodes are independent. So the covariance matrix Σ is rewrite as:

$$\Sigma = \sigma_0^2 \begin{bmatrix} (1+\sigma^2) & 1 & \cdots & 1 \\ 1 & (1+\sigma^2) & \cdots & \vdots \\ \vdots & \ddots & \ddots & 1 \\ 1 & & \cdots & (1+\sigma^2) \end{bmatrix} \tag{15}$$

The ML cost function is the exponent:

$$J_{ML}(\bar{y}) = (H - \Delta)^T \Sigma^{-1} (H - \Delta) \tag{16}$$

From the Eq. 11 and 13, it can be seen that maximizing the likelihood function $f(K, \bar{y})$ is equivalent to minimize the ML cost function (16). Therefore, the target location estimate $\hat{\bar{y}}_{ML}$ is obtained by minimizing the ML cost function :

$$\hat{\bar{y}}_{ML} = \arg\min_{\bar{y}} J_{ML}(\bar{y}) \quad (17)$$

Distributed-centralized processing flow: Considering the above location algorithm is applicable in underwater sensor networks, we adopted distributed-central method to achieve the target localization (Fig. 6). Each node distributedly estimates the $D^{(m)}_i$ through array signal processing and transits the value to sink node by underwater communication and router protocols. After the sink node receives the values, it estimated the target localization by ML methods. The distributed-central method distributes the system compute complex through each node as parallel processing which improves the computation ability rapidly. Comparing with centralized method transmitting the sample data to sink node only, the proposed distributed-central method reduces the data size of communication in underwater sensor networks more, as it transmitting estimation result not but original sample data which resolves the problem on limit of energy and communication band in underwater.

SIMULATION

Extensive simulation runs have been used to testify the validity and study the performance of the target location algorithm in underwater sensor networks which is based on the proposed time synchronization method

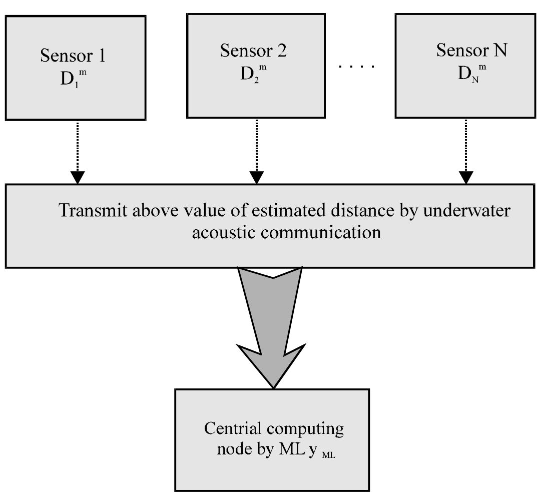

Fig. 6: The method of distributed-centralized for target localization algorithm based on UASN

and underwater acoustic channel model. Let the localization simulation get close to the reality, Firstly, the parameters of underwater node for time synchronization was considered. In this simulation the following parameters about clock in each underwater node were used: the clock offset 12 μ sec, the clock skew 50 ppm. Secondly the algorithm was simulated in 3-D sensor field of size 3000×3000×3000 m with 20 sensors. The node's positions were randomly chosen from the sensor field.

The target location was set (1200, 2100, 1500). We assumed that the variance of measured range is $\sigma_i^2 = \sigma_0^2 = 10\ (i = 2,3 \cdots N)$. We modeled the underwater fading channel with Rician-distributed K = 6 dB (Fig. 4). We conducted 100 repeated trials with above parameters which are based on the above TPUSN algorithm for time synchronization. In each trial, we used Leverberg-Marquardt method to solve the minimization problem based on Eq. 17. Figure 7 showed the 3D-localization performance of the proposed algorithm, the target's position is better estimated with tolerable error for the reality. In order to show the measured RD variance effect on localization performance, Fig. 8 shows the localization error result of proposed algorithm in relation to the changing of the measured range difference of variance by underwater node. The error is the mean error of all nodes between the estimation and actual value in 3-D coordinate and localization error is defined by:

$$e = \text{mean}\{\|\hat{\bar{y}} - \bar{y}\|\}\ .$$

The localization error is the direct proportion to the variance of measured RD.

In order to show the different time synchronization method effect on localization performance based on the proposed algorithm, we simulated the localization error

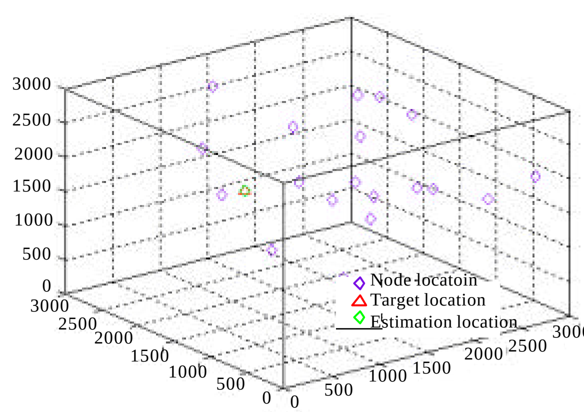

Fig. 7: Target localization 3D simulation in UASN

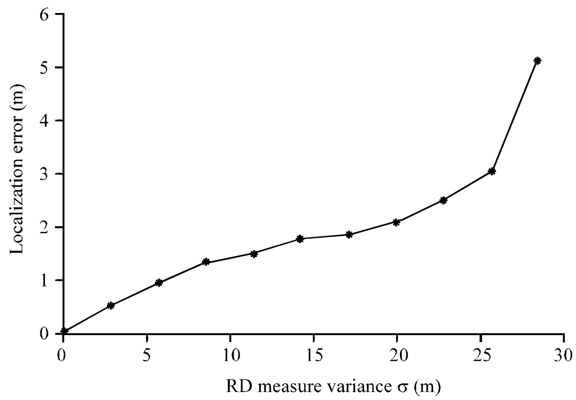

Fig. 8: Location performance with RD variance of nodes with TPUSN time synchronization

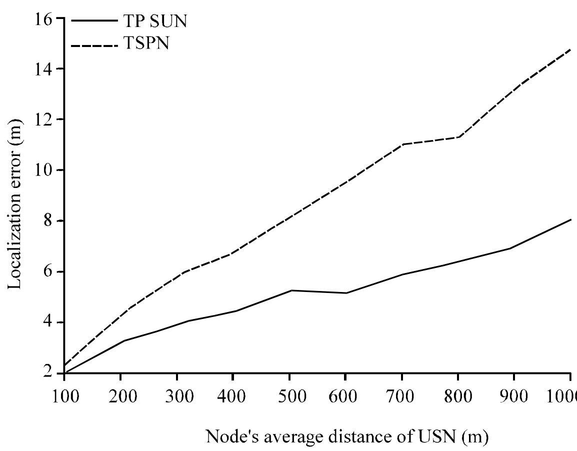

Fig. 9: Location error with underwater node's average distance by different time synchronization methods

with average distance of each underwater node through two different time synchronization methods, TPSN and TPUSN. The simulation result showed that the TPUSN was more suitable to target localization based on proposed algorithms than TPSN in UASN (Fig. 9). As the UASN adopts the TPUSN method to achieve node's time synchronization, the target localization was estimated better and the localization error increased more slowly than TPSN.

CONCLUSION

In this study, the novel target localization algorithm based on time synchronization for underwater acoustic sensor networks was proposed and analysed. The target location was estimated by maximum-likelihood methods based on the Range Difference of Wave Arrival (RDOA) in the condition of time synchronization method TPUSN. Besides, the proposed algorithm adopted the distributed-centralized computation methods which degrade the transmitting energy of underwater sensor networks. The result of simulation has analysed the precision performance of the algorithm with time synchronization and got some instructive conclusions which testify the validity and practicability of the proposed algorithm.

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