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A convolutional neural network machine learning based navigation of underwater vehicles under limited communication

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This paper proposes navigation of multiple autonomous underwater vehicles (AUVs) by employing machine learning approach for wide area surveys in underwater environment. Wide area survey in underwater environment is affected by low data rate. We consider two AUVs moving in formation through clustering followed by selection of optimal path that is affected by low data rate and limited acoustical underwater communication. A state compression approach using machine learning based acoustical localization and communication (ML-ALOC) is proposed to overcome the low data rate issue in which AUV states are approximated by Hierarchical clustering followed by an optimal selection approach using Convolutional Neural Network (CNN). The performance of the proposed state compression algorithm is compared with particle state compression algorithm based on K-Means clustering at each iteration followed by Akaike information criterion (AIC) pursuing extensive simulations, in which two AUVs navigate through trajectory. It is observed from the simulations that the proposed ML-ALOC system provides better estimates when compared with acoustical localization and communication (ALOC) system using particle clustering for state compression scheme.

Key words: Autonomous Underwater Vehicle (AUV), machine learning, hierarchical clustering, Convolutional Neural Network (CNN)

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1. Introduction

AUTONOMOUS underwater vehicles (AUVs) can be deployed in self-organizing tasks in various applications such as marine climate perceptions, exploring benthic resources, studying underwater terrain features and monitoring underwater life, military fields [1–5]. Self-localizing with multiple AUVs is preferred to exhibit ocean floor survey missions and deep-sea mapping operation [6]. Underwater mission planning with multiple AUVs needs cooperative path planning to reduce time and energy costs. These missions are suitable for observing targets using positioning references and limited data processing capabilities in uncertain ocean environment. Cooperative path planning control is a difficult task to achieve due to the uncertainties in AUV dynamics, underwater environment and limited underwater communication range [7, 8]. Again, absence of global positioning system (GPS) signals increases the difficulty in communication in underwater environment. Limited observational coverage degrades the positioning accuracy to track the predefined path.

To resolve these issues, particle filtering and clustering are used for estimating and compressing the data size of the positioning states before transmission and reception in between landmark and moving AUVs [9, 10]. In this research, the acoustical localization and communication (ALOC) system uses particle estimation and particle clustering for compression of data size to exchange between the AUVs. Here, the compression of data consists of three stages such as K-Means clustering, Gaussian approximation followed by selection of optimal state. The state compression algorithm updates new clusters by updating the average of the clusters using K-Means at each iteration and selection of optimal position using Akaike information criterion (AIC) affected by increase in overfitting of the number of free parameters due to approximation. The compression of data size depends on the pre-specified number of clusters size and AIC value to be calculated accurately for statistical model. Multiple AUVs forming arrays to obtain the target energy efficiently by speeding up the formation is proposed in [11]. The extended Kalman filter (EKF) algorithm for state estimation has been proposed using matrices for position estimation [12]. Formation control with communication constraint employing adaptive sliding mode control (adaptive SMC) [13], bionic inspired path planning algorithm [14] and neural network (NN) [15] are proposed for path planning of multiple AUVs with reduced time and energy costs in limited communication range. Selection of a proper underwater communication system is required to reduce delay, low bandwidth and packet loss in underwater region. Therefore, optimal assignment based on positioning in limited underwater communication range poses rapid challenges for navigation of multiple AUVs.

In this paper, machine learning based acoustical localization and communication (ML-ALOC) system replaces particle compression approach of ALOC system with help of machine learning based approach to overcome the issues raised in system as discussed above. The proposed method resolves the stated drawbacks raised due to compressed technique used in ALOC system [10]. In particular, to resolve the first drawback, machine learning as the clustering method is used to remove the pre-specified number of clusters size followed by approximation and convergence. The second drawback is also addressed by proposing the CNN based machine learning approach to resolve the overfitting of increase in approximated free parameters due to optimal selection of positioning data. In the proposed the ML-ALOC system, FSK modulation system in the frequency range 23 to 26 kHz is used to convert the data into transmitting voltage signal so that the signal is transmitted in compressed form in the limited underwater channel.

Note that to design the overall system, the proposed ML-ALOC system is fitted to each AUVs as the transmitting unit. Before transmitting the signal in the channel, it is processed through state estimation and state compression process to reduce the data rate. The moment the transmitting signal reaches for state estimation process both positional parameters and relative positional parameters of the deployed AUVs are determined. For transmission of estimated data, they need to be compressed to reduce the data size for limited range underwater communication. Then, the optimal trajectory generated by mutually shared positional data is regarded as the reference input for the AUVs, where the conventional PID controller controls each AUV.

The contributions of the paper are as follows:

- machine learning based Hierarchical clustering in the compression stage is proposed to accomplish sequential combination of similar clusters until only one cluster is obtained to remove the pre-specified number of clusters size and calculation complexity,
- a pre-trained CNN model followed by the clustering approach is proposed to determine the optimal selection output as weights that are already updated during training set to remove the overfitting of increase in approximated free parameters of estimated data.

The proposed ML-ALOC system fitted in each AUV estimates its position and heading angle with increase in data rate due to state compression using machine learning approach from the horizontal angular velocity under limited communication in acoustic medium.

The paper is organized as follows. The problem statement is discussed in Section 2. The proposed algorithm is discussed in Section 3. Results and discussion are provided in Section 4. The paper is concluded in Section 5.

2. Preliminaries and problem statement

2.1. Preliminaries

As we consider only 3DO F with AUV position and heading angle (yaw) as shown in Fig. 1, so $\eta = [x, z, \theta]^T$, velocity vector $\upsilon = [u, w, q]^T$. The kinematic equations of the AUV can be formulated as [6]

$$M\dot{\upsilon} + C\upsilon + D\upsilon + g(\upsilon) = \tau + \tau_e\,, \tag{1}$$

$$\dot{\eta} = R(\theta)\upsilon. \tag{2}$$

The transformation matrix $R(\theta) = \begin{bmatrix} \cos\theta & \sin\theta & 0 \\ -\sin\theta & \cos\theta & 0 \\ 0 & 0 & 1 \end{bmatrix}$ and $\tau_e = \left[\tau_{du}, \tau_{dw}, \tau_{dq}\right]^T$ represent the force and moments due to external disturbances. The internal matrix M is

$$M(\upsilon) = \begin{pmatrix} m - X_{\dot{u}} & 0 & 0 \\ 0 & m - Z_{\dot{u}} & 0 \\ 0 & 0 & I_{yy} - M_{\dot{q}} \end{pmatrix}. \tag{3}$$

The Coriolis-centripetal matrix C as

$$C(\upsilon) = \begin{pmatrix} 0 & 0 & c_{13} \\ 0 & 0 & c_{23} \\ c_{31} & c_{32} & 0 \end{pmatrix}, \tag{4}$$

where $c_{13} = -c_{31} = -m(x_g q - w) - Z_{\dot{w}} w$, $c_{23} = c_{32} = -m(z_g q + u) + X_{\dot{u}} u$.

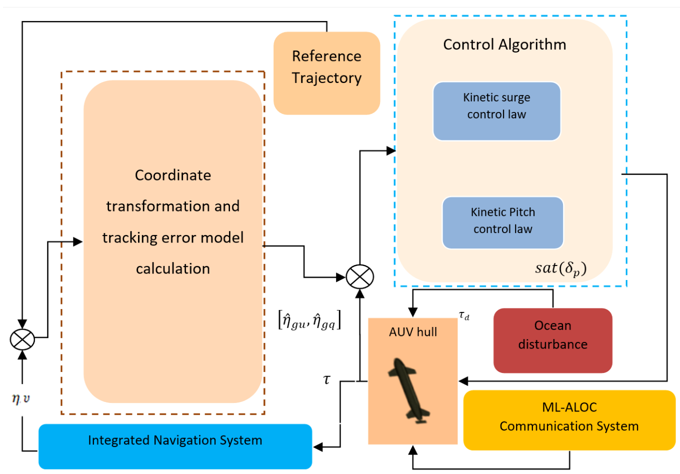


Figure 1: Autonomous underwater vehicle with Communication

The Damping Matrix D is given by

$$D(\upsilon) = \begin{pmatrix} X_u + X_{u|u|}\,|u| & 0 & 0 \\ 0 & Z_w + Z_{w|w|}\,|w| & Z_q + Z_{q|q|}\,|q| \\ c_{31} & M_w + M_{w|w|}\,|w| & M_q + M_{q|q|}\,|q| \end{pmatrix}. \tag{5}$$

The gravitational hydrostatic force vector g is given by

$$g(\upsilon) = \begin{pmatrix} (W - B)\sin\theta \\ -(W - B)\sin\theta \\ (z_g W - z_b B)\sin\theta + (x_g W - x_b B)\cos\theta \end{pmatrix}. \tag{6}$$

The control force for the AUV can be represented as

$$\tau = \begin{pmatrix} F_P \\ Z_{|u|u_{\delta_s}}\,|u|\,u_{\delta_s} \\ M_{|u|u_{\delta_s}}\,|u|\,u_{\delta_s} \end{pmatrix}, \tag{7}$$

where δ_s represents in revolution degree respectively is the angle of stern surface.

Assumptions.

- The trajectory path is continuous and smooth with respect to the reference trajectory and able to differentiable in x and y directions.
- In this research, the disturbances due external forces dynamics and the errors in modeling are bounded with constants such as, $|du| < Du$, $|dw| < Dw$ and $|dq| < Dq$.
- The kinematic model is smooth for hydrodynamic parameter.
- The weight w^* and b^* are bounded for approximation of convolutional neural network system.

2.2. Problem formulation

Underwater environment is uncertain and hostile in nature. There are different types of underwater environment including near shore and polar ice caps. AUVs are employed in all types of marine environment to accomplish different missions such as scientific, military and commercial. In the proposed technique [10], two AUVs (AUV A and AUV B) have been deployed for the mission under limited underwater communication range. They alternate their role as “moving role (MR)” and “landmark role (LR)” by maintaining minimum positioning error to move in a wide ocean area as shown in Fig. 2. The MR deployed AUV guided by the relative position of the LR deployed AUV using estimation of positioning information such as its position and heading angle (yaw) may be mutually shared among themselves using optimal compression technique. To obtain an ideal transmission of positioning information, an optimal selection of state compression model may be proposed to minimize the above time required for role exchange and occupancy communication time with low positioning error under limited underwater communication range.

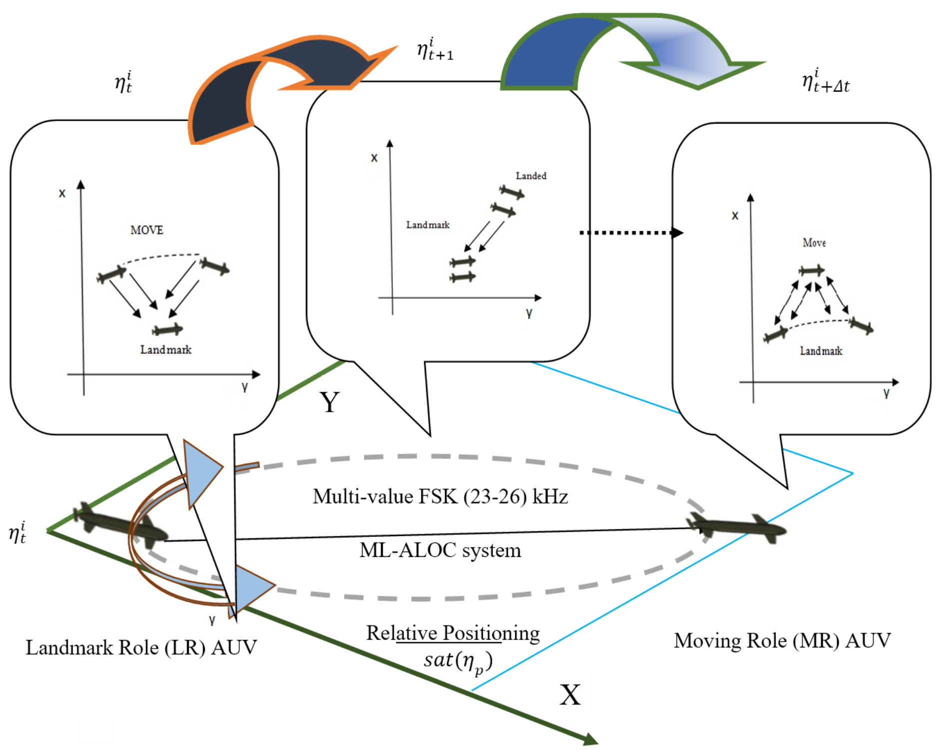


Figure 2: Alternating the role as moving role (MR) and landmark role (LR) deployed AUVs

2.3. Limited underwater communication

Underwater communication is needed to provide information exchange between multiple AUVs. In this research, two main challenges in underwater acoustic communication are considered such as communication time for role change between the deployed AUVs and limited communication range. A combination of state estimation and state compression may be implemented to perceive the communication between the MR deployed AUV and LR deployed AUV under the limited underwater communication range. The mutual acoustic positioning data needs to be estimated by using particles filtering technique because in a nonlinear filter, positioning states are represented by a nonparametric model and can be expressed complicated state distributions. To obtain a fast transmission of positioning information, the estimated positioning data are then compressed the data size through clustering and selection of optimal model while changing the LR role for the deployed AUV [10].

State estimation and compression

We consider three DOF by estimating position and heading angle represented as x, y and ψ respectively. The MR deployed AUV estimate the three parameters for itself and LR deployed AUV through navigation sensors fitted with both the AUVs. In the proposed method, particle filtering that provides the probability density of a set of states using stochastic method [10, 13]. The states at time t are represented as $\eta_t = \left\{\eta_t^i \mid i = 1, \ldots, n\right\}$ where the state for the i-th particle is expressed by

$$\eta_t^i = \left[\eta_t^{MRi}\ \eta_t^{LRi}\right]^T, \tag{8}$$

where $\eta_t^{MRi} = \left[x_t^{MRi}\ y_t^{MRi}\ \psi_t^{MRi}\right]^T$ denoted as the position in X, Y direction and yaw angle for moving role (MR) deployed AUV and $\eta_t^{LRi} = \left[x_t^{LRi}\ y_t^{LRi}\ \psi_t^{LRi}\right]^T$ denoted as the position in X, Y direction and yaw angle for landmark role (LR) deployed AUV. The landmark role between the AUVs in low data rate of 100 bps of multiple-value FSK system in underwater environments gets exchanged with the moving role AUV. To overcome such low data rate problem, the estimated states are compressed before transmission. Therefore, machine learning based approach such as Hierarchical clustering followed by convolutional neural network (CNN) is proposed to compress the estimated states for mutual acoustical positioning between the deployed AUVs. K-means clustering initially classified together with one centroid and might be redirected to another one after reiteration during the operation of compression of the estimated position. Again, it is quite difficult to predict the K-value and the method does not work in global cluster. So, an unsupervised machine learning algorithm may be used to group the unlabeled estimated data merging them until one cluster as Hierarchical clustering method. Then the optimal model may be selected through CNN algorithm to avoid the free parameters increased due to the approximation.

3. Proposed ML-ALOC system

Figure 3 represents the complete block diagram of machine learning based acoustical localization and communication (ML-ALOC) system. The transmitting unit includes multiple values FSK modulation system, DC power supply, amplifier, and transmitting signal.

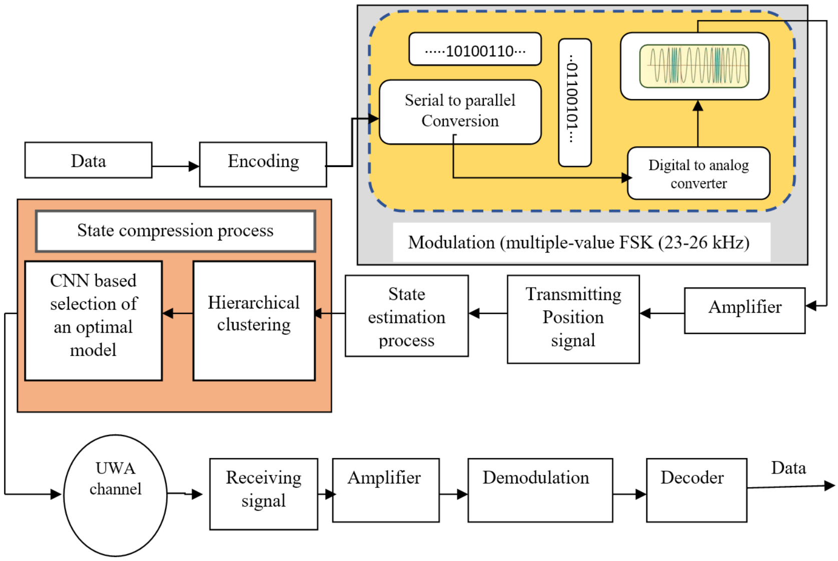


Figure 3: Design of ML-ALOC system using multiple-value FSK

In the ML-ALOC system, the data is first converted into binary streams and then converted the data into transmitting voltage signal so that the signal is transmitted through the underwater channel using multiple values FSK modulation system in the frequency range 23 to 26 kHz. Before transmitting the signal in the channel, it is processed through state estimation and state compression process to reduce the data rate. The moment the transmitting signal reaches for state estimation process both positional parameters and relative positional parameters are determined. For transmission of estimated data, they need to be compressed to reduce the data size for limited range underwater communication. The transmitted data received at the receiving unit that includes amplifier, analog-to-digital (ADC) converter followed by the decoder. Transmitted through an underwater channel, the transmitted voltage signal is attenuated severely in underwater environment. The amplifier then amplifies the attenuated signal and then fed to the detection device with a sufficient level of intensity. The amplified signal processed through the ADC and then passes to decoder for the recovered data. The system transmits the data through three phases: Multi-value FSK System, state estimation and state compression.

3.1. Multi-value FSK system

Multi-value FSK modulation system is used in ML-ALOC system as it detects the attenuated signal easily and reduces bit error rate. Second advantage of using multi-value FSK system is that it has a better anti-interference ability and is a low complex modulation system [9, 16]. It uses frequency modulation technique digitally to transmit information [17]. The frequency of carrier signal is controlled by transmitted digital information during modulation. The frequency in the range 23 to 26 kHz is used to represent different symbols. As the changes between the frequencies are instantaneous, therefore, it is more resistant to interference. Multiple numbers of carriers are used to carry the symbol information in multi-value FSK system; therefore, it is useful to decrease the bit error rate after passing through long distance in underwater environment. The data rate of 100 b/s may be considered for the proposed ML-ALOC system using chirp signals of 8 B as data size. With the help of one transmitter and four receivers that are fitted in each AUV, enable the communication and trans-reception of positional data among themselves.

3.2. State estimation

The state of the AUV's in 3DOF are the horizontal positional parameters and can be evaluated as x, y and yaw (ψ). This study assumes two AUVs such as MR deployed AUV and LR deployed AUV.

The velocity at ground and angular velocity are assumed to be zero for LR deployed AUV (as stationary on the seafloor). The estimation is done by the proposed ML-ALOC system fitted to each AUV and the MR deployed AUV determines both positional parameters of its own and relative positional parameters of LR deployed AUV as shown in Fig. 4. The particle filter uses a set of particles for state estimation using the probability density of the positioning state [10, 15]. The states at time t are represented as (8) $\eta_t^i = \left[\eta_t^{MRi},\ \eta_t^{LRi}\right]^T$ the ground velocity $\hat{v}_t$, and the angular velocity $\hat{w}_t$. Then the mutual acoustic positioning states such as relative distance, $\hat{r}_t$, the relative directions from MR deployed to LR deployed AUV $\hat{\theta}_t^{ML}$ and LR deployed to MR deployed AUV $\hat{\theta}_t^{LM}$ are updated. The time required to transmit the positioning signal is at t second from the MR deployed AUV receives the feedback and update the position at $t + \Delta t$ second from the LR deployed AUV as shown in Fig. 2. The state of moving AUV represented as η in 3DOF may be updated as

$$\eta_{t+1}^{MRi} = \eta_t^{MRi} + R\left(\psi_t^{MRi}\right) v_t^{MRi} \Delta t, \tag{9}$$

$$\psi_{t+1}^{MRi} = \psi_t^{MRi} + w_t^{MRi} \Delta t \tag{10}$$

$$v_t^{MRi} \sim N\left(\hat{V}_t^{MR},\ (\sigma_{vt}^{MR})^2\right), \tag{11}$$

$$w_t^{MRi} \sim N\left(\hat{\omega}_t^{MR},\ (\sigma_{\omega t}^{MR})^2\right), \tag{12}$$

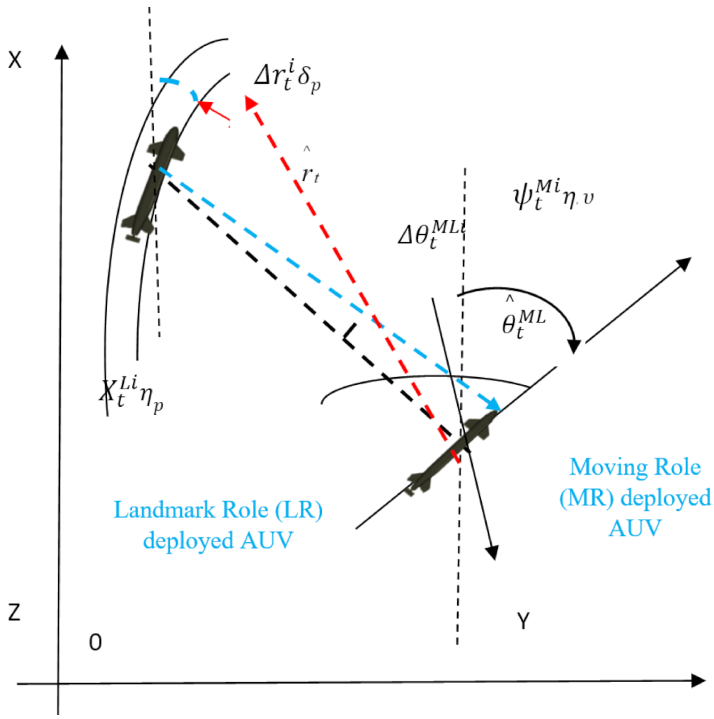


Figure 4: Measurement of states and mutual positioning by the deployed AUVs

where R denotes rotation matrix and the Gaussian sampling $N(\mu, \sigma^2)$ with mean μ and variance σ^2. The updating process between the two AUVs is effective when the relative distance and relative direction have estimated successfully. Based on the likelihoods $L\left(\eta_t^i\right)$ estimated data each AUV and the next position η_{t+1} is determined with the help of weight function ω_t^i as

$$\omega_t^i = L\left(\eta_t^i\right) = L_{ML}\left(\eta_t^i\right) L_{LM}\left(\eta_t^i\right), \tag{13}$$

where ω_t^i are the weight of the i-th particle. L_{ML} and L_{LM} are the relative measurements collected by the MR to and LR to respectively. The likelihood $L_{ML}\left(\eta_t^i\right)$ and $L_{LM}\left(\eta_t^i\right)$ may be calculated from relative measurement from MR deployed AUVs and LR deployed AUVs as provided in [10]. In the transmitting signal time t second may be considered for updating received signal time $t + \Delta t$, the offsets for distance Δr_t^i and direction $\Delta\theta_t^{MLi}$ may be calculated as

$$\Delta r_t^i = \left| \frac{\left|\eta_{t+\Delta t}^{Li} - \eta_{t+\Delta t}^{MRi}\right| + \left|\eta_t^{LRi} - \eta_t^{MRi}\right|}{2} - \hat{r}_t \right|, \tag{14}$$

$$\Delta\theta_t^{MLi} = \left| \arg\left(\eta_{t+\Delta t}^{Li} - \eta_{t+\Delta t}^{MRi}\right) - \left(\psi_{t+\Delta t}^{MRi} + \hat{\theta}_t^{ML}\right) \right|, \tag{15}$$

$$\Delta\theta_t^{LMi} = \left|\arg\left(\eta_t^{Mi} - \eta_t^{LRi}\right) - \left(\psi_t^{LRi} + \hat{\theta}_t^{LM}\right)\right|. \tag{16}$$

In the limited communication, if the positioning measurements are not obtained, then $\omega_t^i = 1$ and $L\left(\eta_t^i\right)$ remain unchanged.

3.3. State compression

When landmark role is exchanged, the estimated states is shared by the moving AUV. Low data rate of acoustic communication restricts the constant state sharing in underwater environments. Therefore, it is necessary to compress the estimated states before transmission of information. Hence, the state compression is included in ML-ALOC system, which is achieved through Hierarchical clustering followed by selection of optimal model. The selection of optimal model is achieved using CNN, which is used to overcome the lacuna of overfitting of free parameters estimated after approximation.

Hierarchical clustering

Hierarchical clustering is a structure of clustering consisting of nested partitions based on machine learning approach. Every time, similar cluster pairs are combined, and this step is repeated until all the positioning data are in a single cluster [18, 19]. No a-priori information about the number of clusters are required in this proposed clustering compared to K-Means clustering approach. The states (particles) of the AUVs are combines by means of hierarchical clustering into a single cluster. Each estimated state is considered as a cluster. Initialization for the distance matrix proceeds as follows

1. Let the first center and second center is μ_i and μ_j respectively selected from the each estimated state cluster.
2. The mean distance d_{mean} between the two centroids is represented as

$$d_{\text{mean}}\left(C_i,\ C_j\right) = d(\mu_i,\ \mu_j), \tag{17}$$

where C_i and C_j represents the distance matrix coordinates,

$$\mu_i = f\left(\eta_t^{MRi},\ \eta_t^{LRi}\right), \quad i = 1, \ldots, n, \tag{18}$$

$$\mu_j = f\left(\eta_t^{MRj},\ \eta_t^{LRj}\right), \quad j = 1, \ldots, n. \tag{19}$$

Enrollment in local colleges, 2005

Algorithm 1. Proposed Hierarchical clustering

Step 1:	Set the state of particles as $\eta = \{\eta_t^1, \eta_t^2, \ldots, \eta_t^i\}$ and treat each particle as cluster.
Step 2:	Start with disjoint cluster with level $L(0) = 0$ and sequence number $s = 0$.
Step 3:	Determine the centroids of each cluster. Find the least distance centroids in the current clustering, say (μ_i) centroid in cluster (i) and (μ_j) centroid in cluster (j).
Step 4:	Determine $d_{\text{mean}}(C_i, C_j) = d(\mu_i, \mu_j)$ as given in [17].
Step 5:	Sequence number may be incremented as $s = s + 1$. Merge clusters (i) and (j) into a single cluster to update next clustering s. Set the level of the clustering to $L(s) = d[(i), (j)]$.
Step 6:	The row and column corresponding to clusters (i) and (j) is added to the rows and columns corresponding to new cluster to update the distance matrix (d_{mean}).
Step 7:	If all the data points are in one cluster, then stop, else repeat from step 3.

Selection of optimal model using CNN

The original particles are grouped together into a cluster by means of hierarchical clustering. During communication for a particular time, a state for MR and LR will be selected through selection of optimal model.

Figure 5 shows the proposed model using CNN for achieving compression. During training set the CNN network ask whether the process is end or not but during testing time directly it will generate the output as weights are already updated during training set [20, 21]. CNN has the ability to represent a network

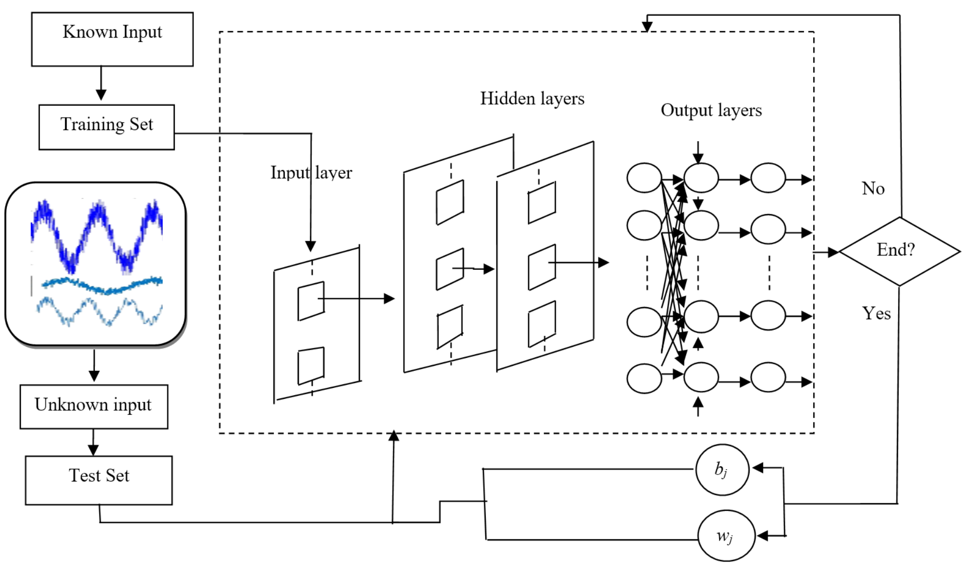


Figure 5: Selection of optimal state for achieving compression using CNN

in a better generalized way compared to fully connected networks [18]. The proposed CNN model consists of an input layer, two hidden layers, and an output layer. The CNN has four layers in total, and each layer contains four neurons to determine a state with low bit error rate in a particular time. The result of convolution between input layer and hidden layer is mathematically expressed as:

$$X^P = \left(X^{P-1} * W_1^P\right) + b_1^P\,, \tag{20}$$

where X is the output feature map, X^{P-1} is the input, P is the number of layers, W_1 is the filter or kernel slides over input image, $*$ denotes the convolution operation, b_1 is the bias. The matrix X^{P-1} is generated using the parameters of all states generated after hierarchical clustering

$$X^{P-1} = \begin{bmatrix} x_t^{MR1} & y_t^{MR1} & \cdots & \psi_t^{LR1} \\ x_t^{MR2} & y_t^{MR2} & \cdots & \psi_t^{LR2} \\ \vdots & \vdots & \vdots & \vdots \\ x_t^{MRi} & y_t^{MRi} & \cdots & \psi_t^{LRi} \end{bmatrix}. \tag{21}$$

In the classification stage in CNN, the desired output from a fully connected layer is mathematically expressed as

$$\hat{O}_j = \left(w_j^T,\, X_j\right) + b_j\,, \tag{22}$$

where $j = 1, 2, \ldots, 6$, b_j represents the bias constant in classification stage, X_j epresents the input to a fully connected layer which is obtained from the convolution between input layer and hidden layer, w_j is the weight matrix in a fully connected layer. The error at the output layer is represented as

$$e_j = O_j - \hat{O}_j\,. \tag{23}$$

Algorithm 2. Proposed CNN based Machine Learning approach

Step 1:	Set the parameters of all states in a matrix form as represented in (21).
Step 2:	Start the 1st convolution process between input and hidden layer using (20) with a filter or kernel size of 11×11.
Step 3:	Start the 2nd convolution process between input and hidden layer using (20) with a filter or kernel size of 5×5.
Step 4:	Give the desired collected feature obtained from convolutional layer to output layer and compare with actual feature using (23).
Step 5:	Minimize the error by updating weights and bias constant.
Step 6:	If the error minimizes, then input the test set else go to step 5.

4. Results analysis discussion

To verify the efficacy of the proposed ML-ALOC using Hierarchical clustering followed by a pre-trained CNN model compared with the ALOC system followed by the particle clustering [10], MATLAB simulations and experiments are carried out to compress the data size. A comparison of the proposed ML-ALOC system and ALOC system using Particle clustering is provided in Table 1.

Table 1: Comparison of the proposed ML-ALOC system and Particle clustering using ALOC system [10]

ALOC system using particle clustering [10]	Proposed ML-ALOC system
Step 1: Communication Technique	
Acoustical localization and communication (ALOC) system is implemented for positioning and Communication [9].	Machine Learning based acoustical localization and communication (ML-ALOC) is proposed for positioning and Communication.
Step 2: State Estimation	
Estimation of position of the deployed AUVs is carried out based on prediction phase and observation phase using Particle filtering approach [10].	Same particle filter is realized to estimate the position of the deployed AUVs using BELLHOP simulator, which is stable and robust against underwater noises and limited communication.
Step 3: State Compression	
Particle clustering approach is used to compress the estimated data size by K-means clustering, Gaussian approximation and AIC based optimal selection approach.	A machine learning based Hierarchical clustering approach is used for clustering followed by CNN approach for compressing the estimated data size.

In the simulation, there are two AUVs operating in a space of 300×300 m^2 area as shown in Fig. 6. These AUVs track the desired path using various positions assigned through particle filter estimation followed by compression of positioning data as shown in the Fig. 6. The blue line and red line indicate the desired path for AUV A and AUV B respectively as shown in the figure. The initial position of the AUV A and AUV B is considered as $(0, -5, 0)$ and $(0, 5, 0)$ respectively with a speed of 0.3 m/s each. The number of states is set to 1000 from the particle filter to be transmitted for mutual acoustical positioning based on the number of clusters ($c = 1, 2, 10$) available in the operating space. Then, the MR deployed AUV exchange their role at seafloor by transmitting compressed positioning data to LR deployed AUV. The parameters used for implementation of the proposed work using MATLAB based on BELLHOP simulator is given in Table 2.

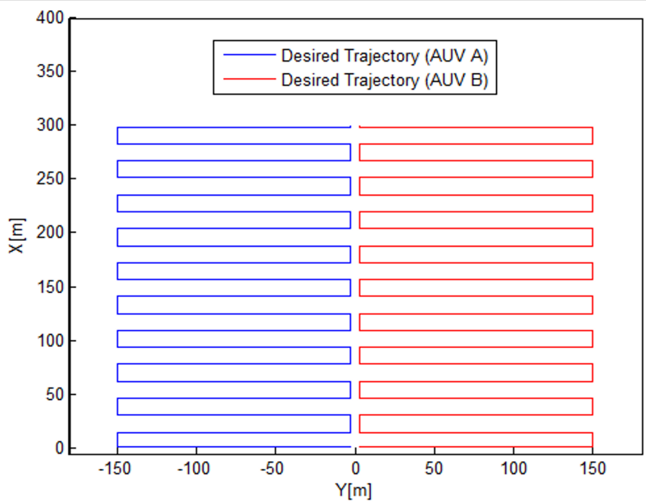


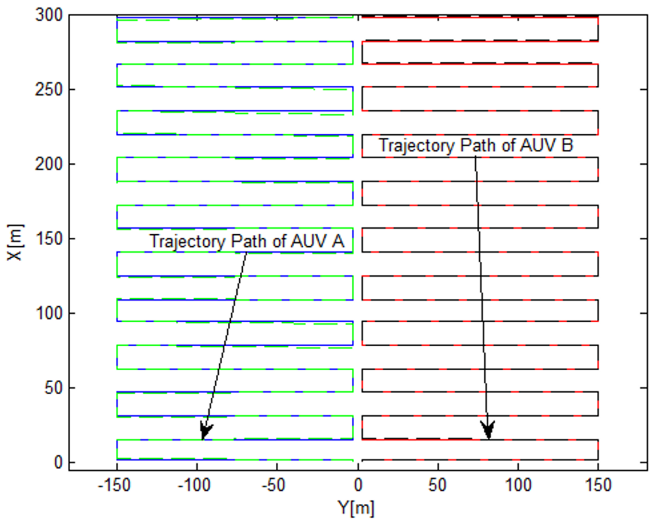
Figure 6: Desired trajectories for AUVs

Table 2: Specifications used in simulation setup based on BELLHOP

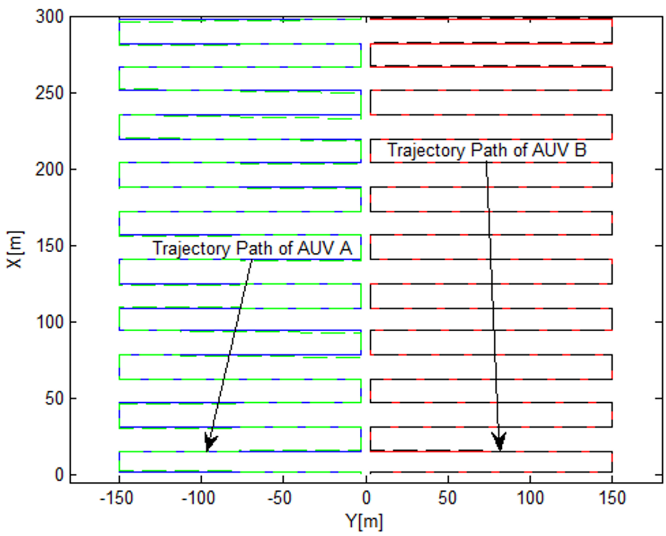
Stage	Specification of parameters	Values
Multi-value FSK communication system	Frequency	23–26 kHz
	Data rate	100 bps
	Data size	8 bytes
	Standard deviation of distance between the of stationary ML-ALOCs	0.021 m
	Distance between the stationary AUVs during positioning measurement	30 m
	Standard deviation of direction between the of stationary AUVs	0.166°
Estimation and compression	Prediction phase interval	1 s
	Positioning chirp	22–28 kHz
	Occupancy time (both positioning and data communication)	4 s
	Observation phase for positioning	10 s
	Compressed state communication interval (before exchanging their roles)	4 s

BELLHOP simulation system is used to set up an underwater multi-value FSK network as given in Table 2 but the data analysis for optimal solution is performed using MATLAB [22–24]. The proposed method is evaluated and tested in MATLAB simulation and its results compared with the ALOC system using particle-clustering approach [10].

The AUVs are assumed to be connected and share the positioning information at all the time. The trajectories of the AUVs for both the method are plotted in Fig. 7. The AUVs clearly track the desired path and the estimation errors in terms



(a)

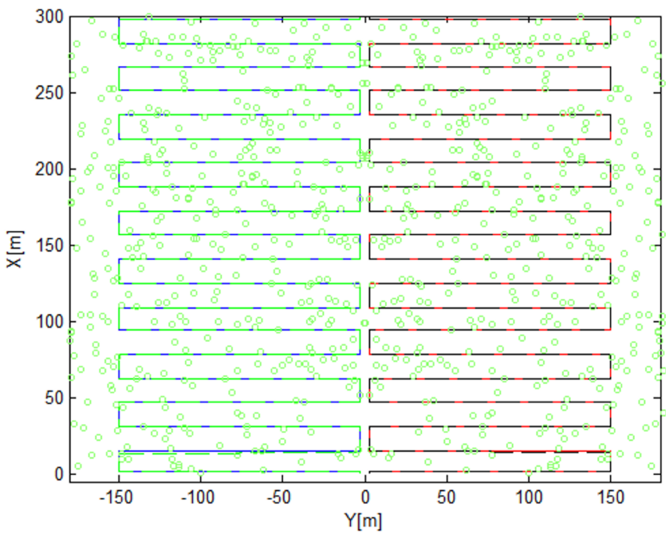


(b)

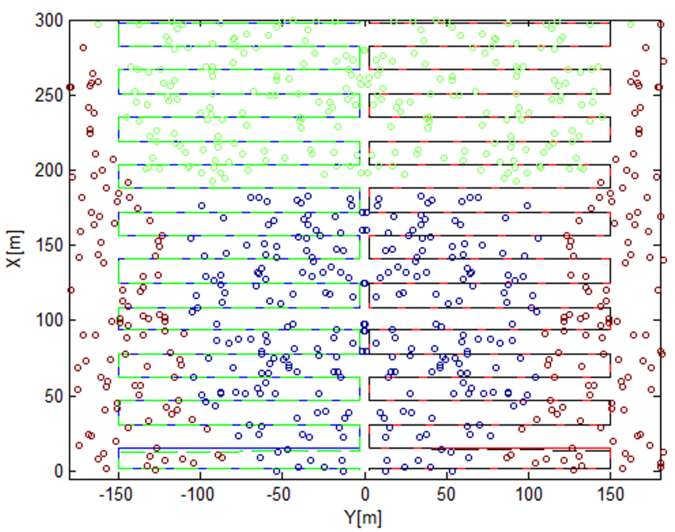
Figure 7: Trajectories of AUVs (a) ALOC system using particle clustering, (b) the proposed ML-ALOC method

of X position, Y position, and yaw angle are calculated as 0.15 m, 0.3 m, and 0.1° respectively. During the role exchange to LR, the moving AUV revised the estimation states and errors relative to LR deployed AUV.

To explore the influence of cluster size on the training of optimal CNN model, we test different input permutations in the form of positional data using clusters as shown in Fig. 8. The proposed ML-ALOC system is developed for the mutual

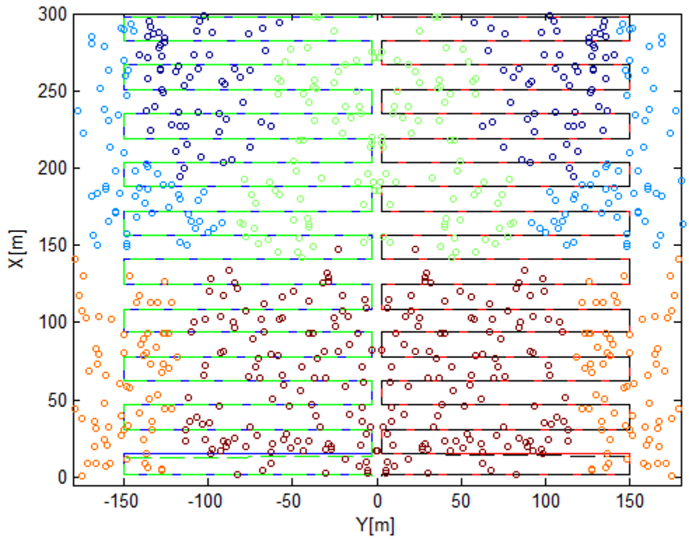


(a)

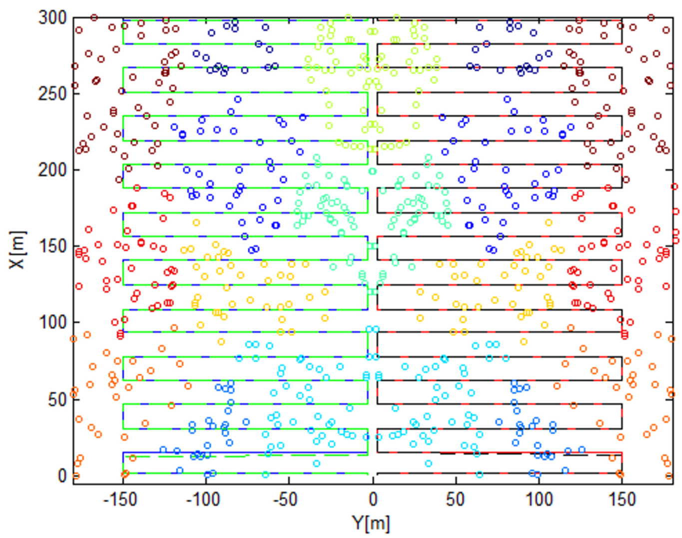


(b)

Fig. 8 (a), (b)



(c)

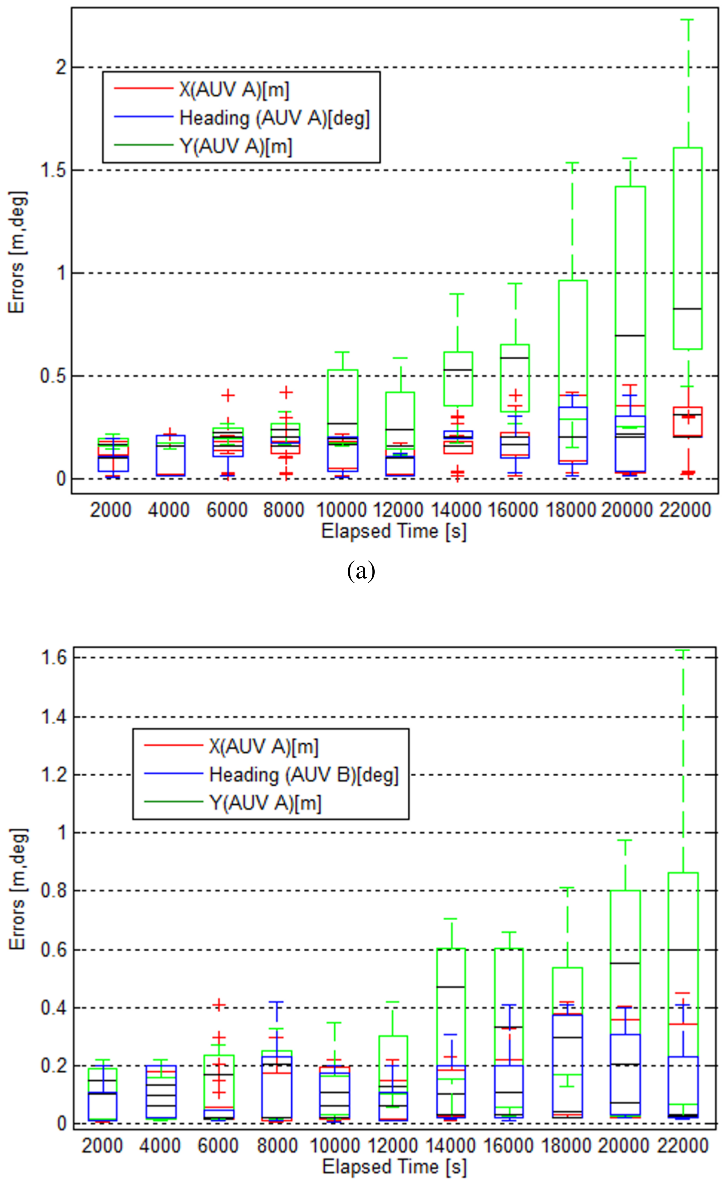


(d)

Figure 8: Trajectories of AUV based on the proposed ML-ALOC method using (a) one clusters, (b) three clusters, (c) five clusters, (d) ten clusters

acoustical localization and communication using Hierarchical clustering method. From Fig. 8, it is observed that with increase in cluster size the accuracy to follow the trajectory increases. The increase in number of clusters subdivides the area of mission into small partitions to provide better underwater communication coverage. The MR deployed AUV shares the positioning states before role exchange with the LR deployed AUV.

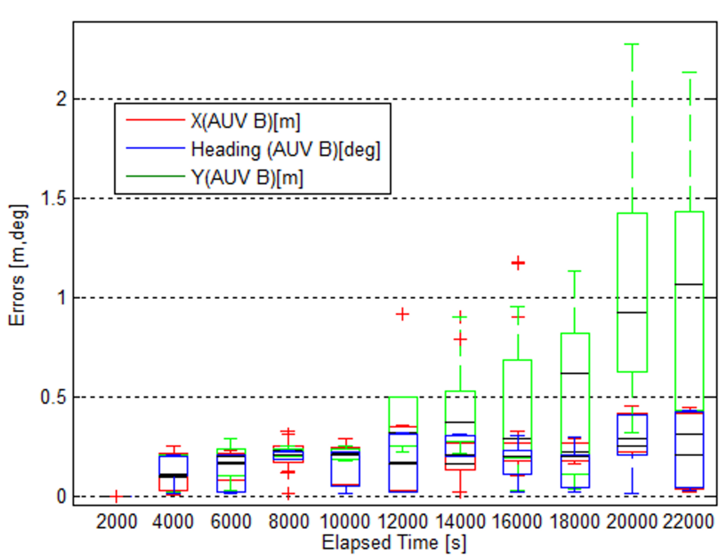
Moreover, the superiority in compression of data size using the proposed machine learning based CNN algorithm is demonstrated as shown in Fig. 9 to



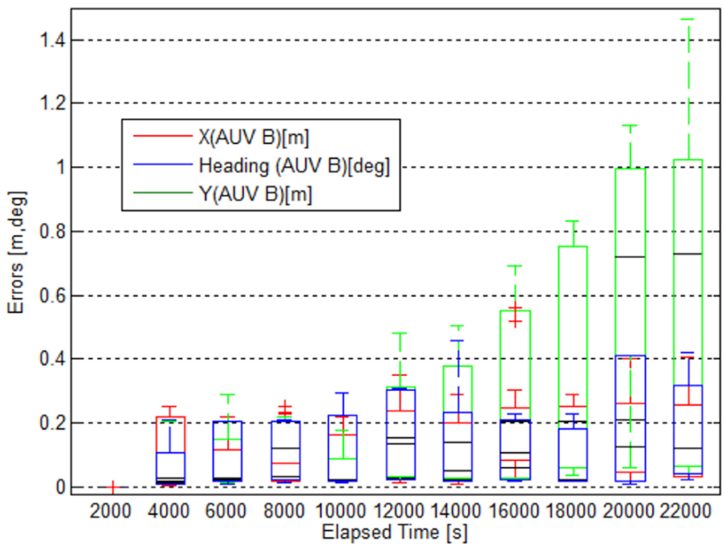
(b)

Fig. 9 (a), (b)

Fig. 13. Figures (a, b) correspond to AUV A, while Figs. (c, d) correspond to AUV B in Figs. 9–13. Error [positional data, yaw angle] versus elapsed time are analyzed using Boxplots that graphically depicts groups of numerical positional



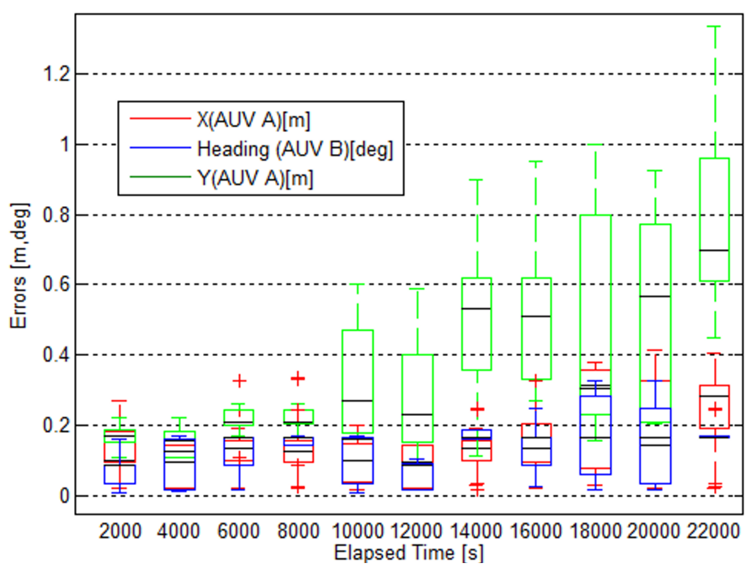
(c)



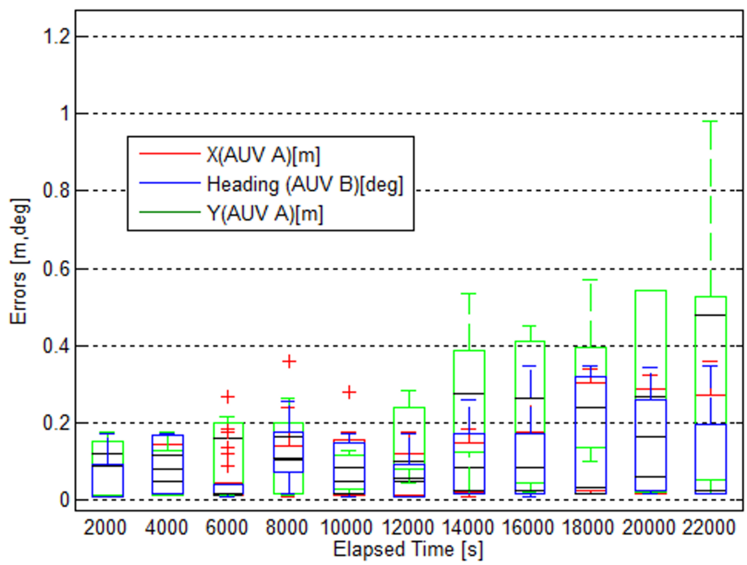
(d)

Figure 9: Error estimation for X position, Y position and yaw angle using one cluster for (a) and (c) ALOC system using particle clustering (b) and (d) the proposed ML-ALOC method

data through their quartiles. Twenty simulations are performed in each case with varying the cluster from one to ten. The proposed ML-ALOC method consistently exhibits smaller error bars in the form of whiskers across all scenarios in (b) and



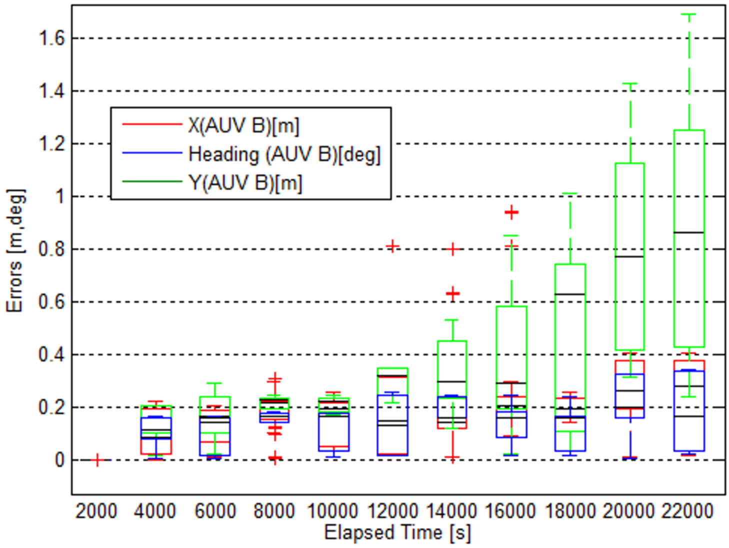
(a)



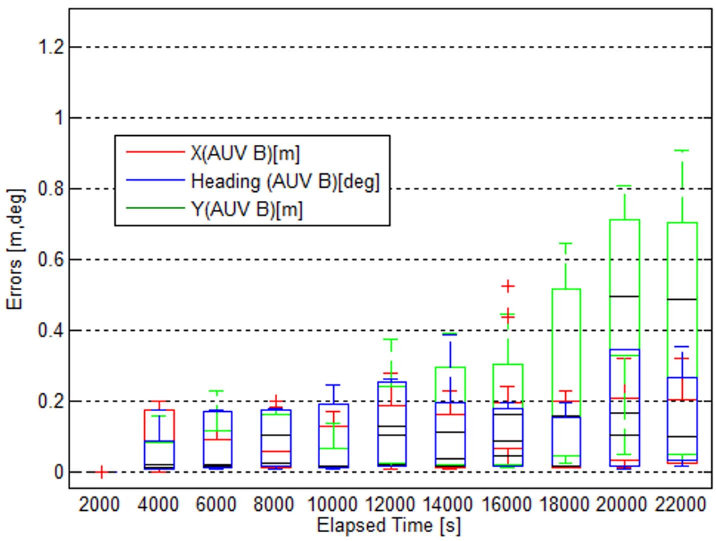
(b)

Fig. 10 (a), (b)

(d) compared to the ALOC system with particle clustering in (a) and (c), as shown from Fig. 9 to Fig. 13 with varying cluster sizes. Whiskers indicate variability outside the upper and lower quartiles of errors and the range is one-and-a-half



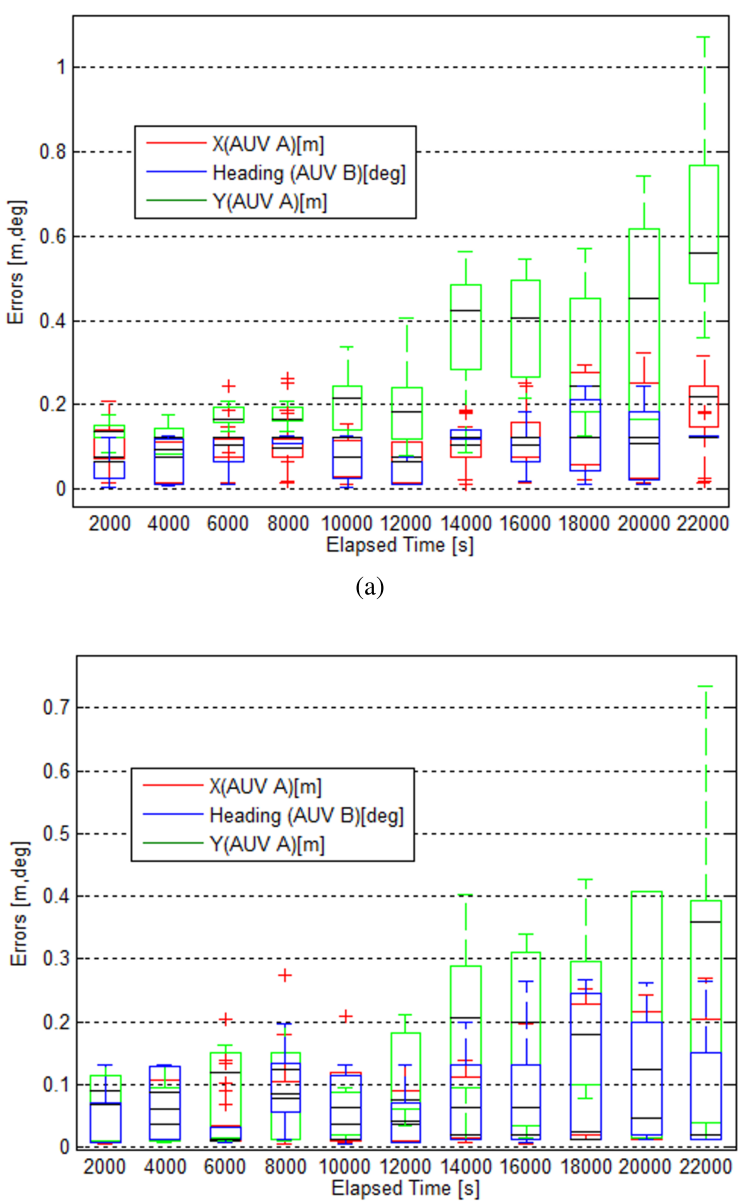
(c)



(d)

Figure 10: Error estimation for X position, Y position and yaw angle using three clusters for (a) and (c) ALOC system using particle clustering (b) and (d) the proposed ML-ALOC method

interquartile range. Data outside the whisker are plotted as '+'. With increase in cluster size, the errors of *X* position, *Y* position and yaw angle in the proposed method are smaller. Therefore, it can be determined from the analysis that the

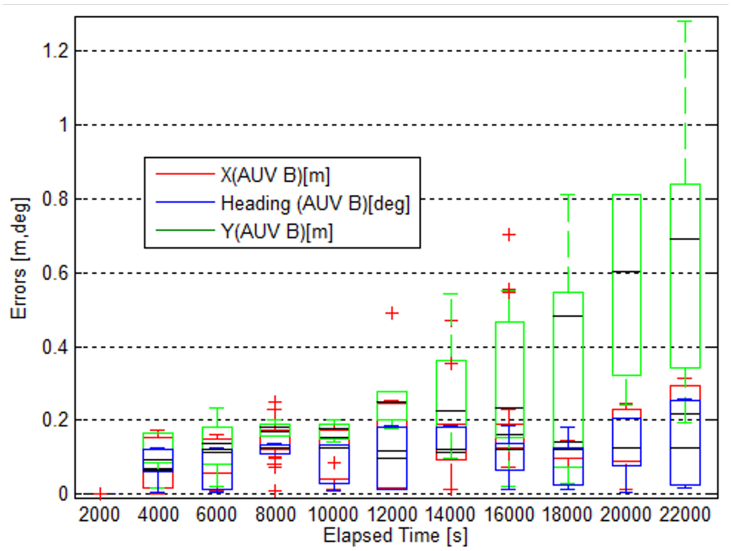


(a)

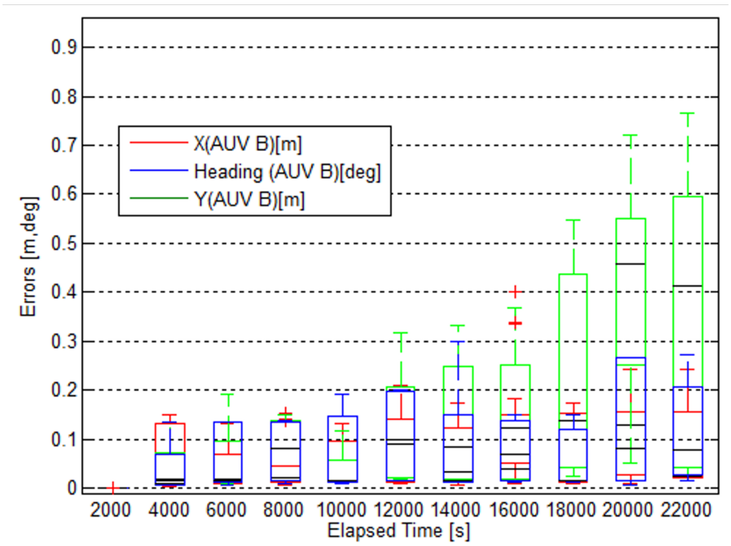
(b)

Fig. 11 (a), (b)

estimated signals can be compressed by the proposed method. The Boxplot for estimation of errors in X position, Y position and yaw angle are determined as the AUVs exchange the landmark role accordingly with the cluster size and the CNN



(c)

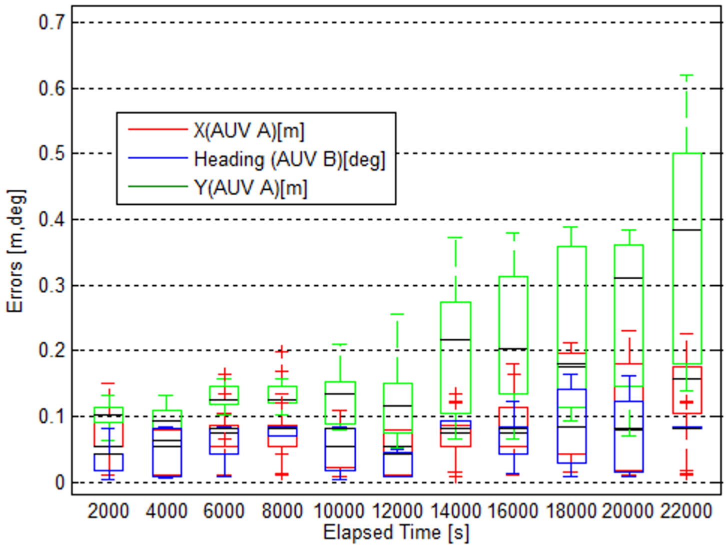


(d)

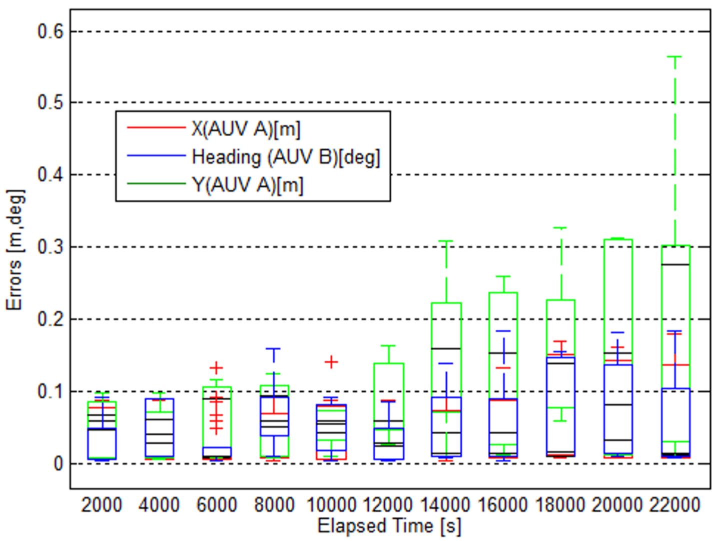
Figure 11: Error estimation for X position, Y position and yaw angle using five clusters for (a) and (c) ALOC system using particle clustering (b) and (d) the proposed ML-ALOC method

based state compression technique as shown in Fig. 9 to Fig. 13. The advantages of the proposed technique are

- the errors are smaller in the proposed technique while states are completely estimated.



(a)

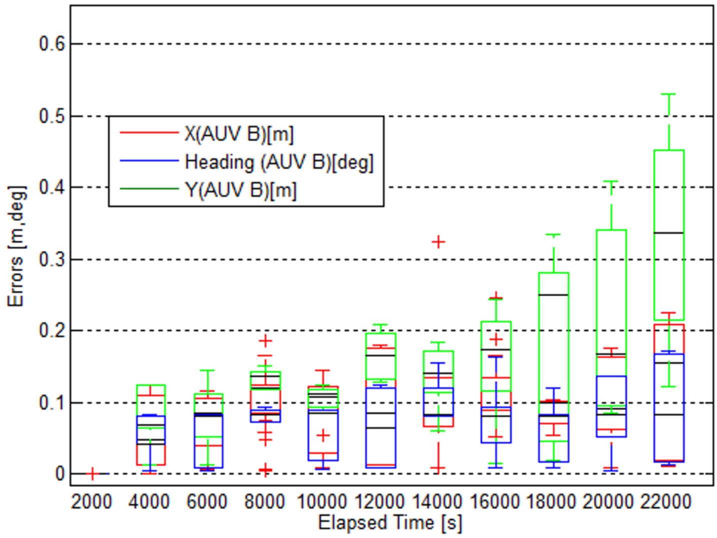


(b)

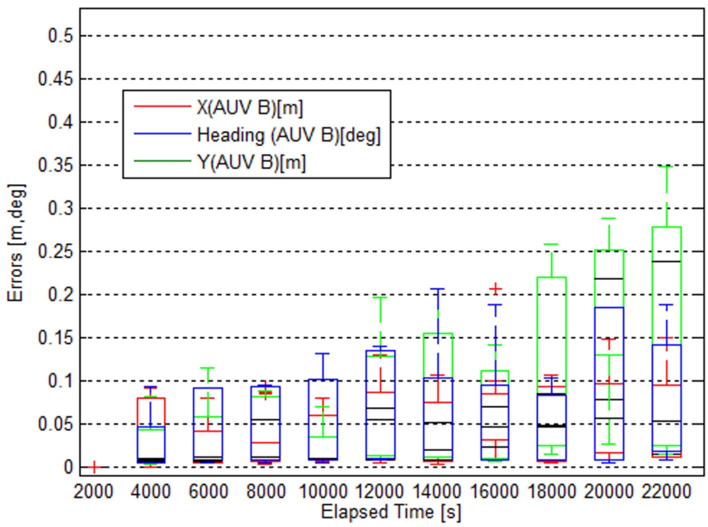
Fig. 12 (a), (b)

- no need to calculate the maximum cluster size, which is the advantage of using machine learning based Hierarchical clustering.

Communication time per role exchange with increase in size of the clusters is simulated and presented in Fig. 14a. Again, occupancy of the entire commu-



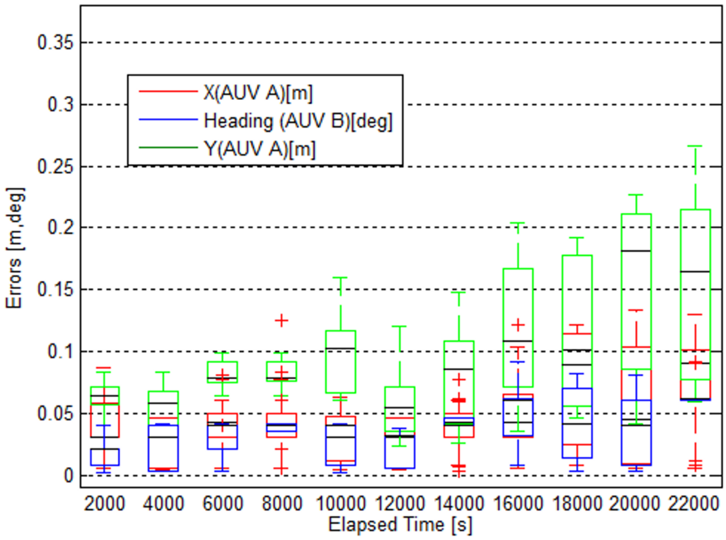
(c)



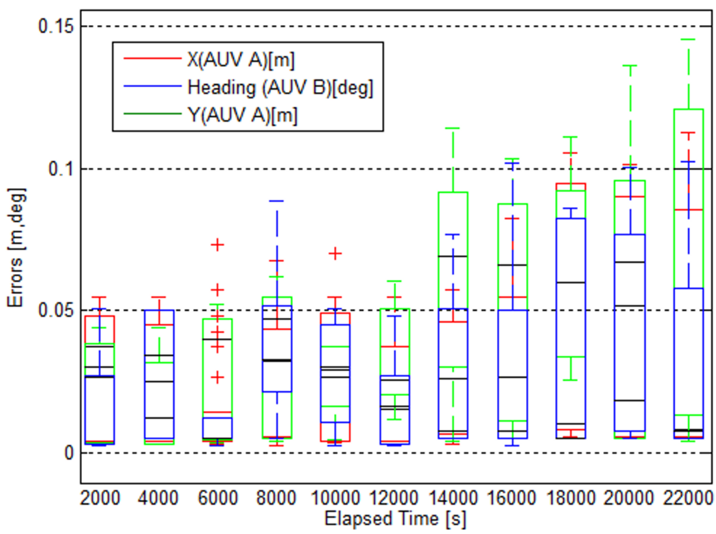
(d)

Figure 12: Error estimation for X position, Y position and yaw angle using eight clusters for (a) and (c) ALOC system using particle clustering (b) and (d) the proposed ML-ALOC method

nication time for each cluster size is presented in Fig. 14b. The required time occupancy and the communication time increase with increase in cluster size for both the method but the proposed ML-ALOC method is almost (3/4)-th times



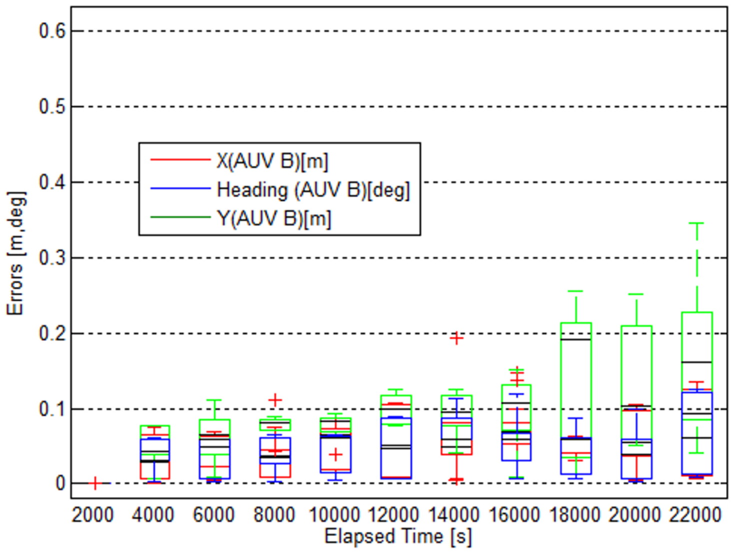
(a)



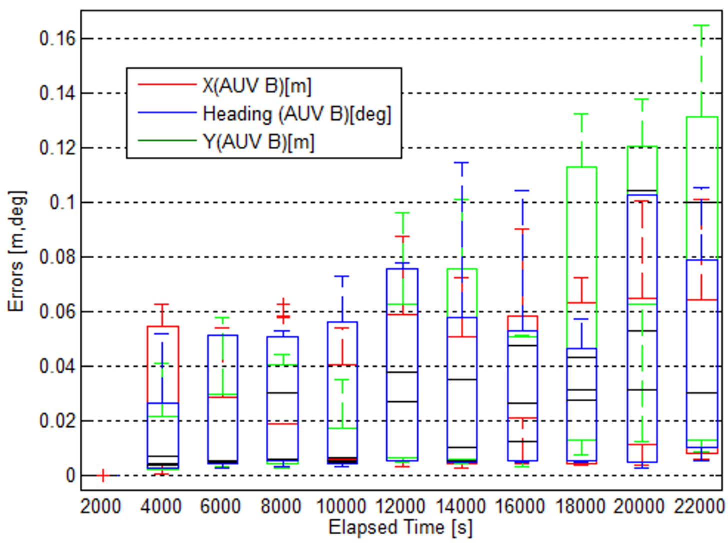
(b)

Fig. 13 (a), (b)

better that results in increase in data rate. On comparing both the methods, the advantage of proposed method is independent of the cluster size.

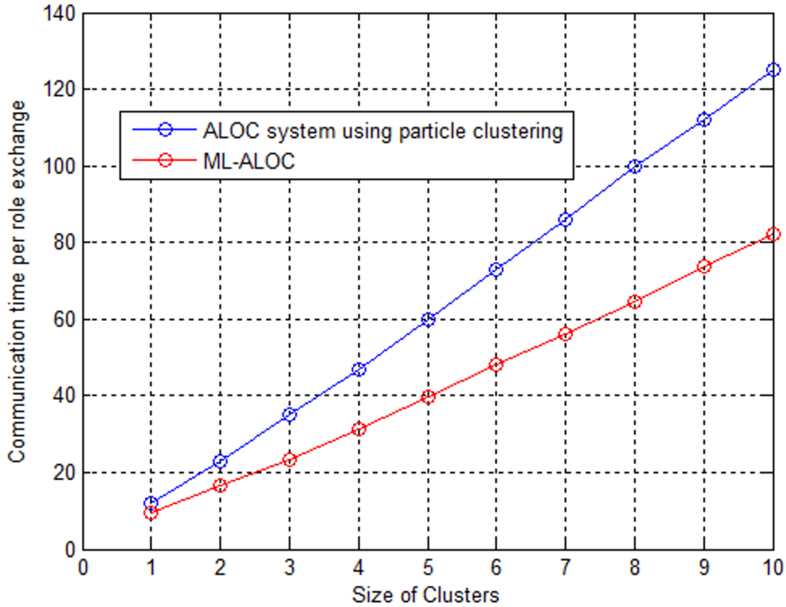


(c)

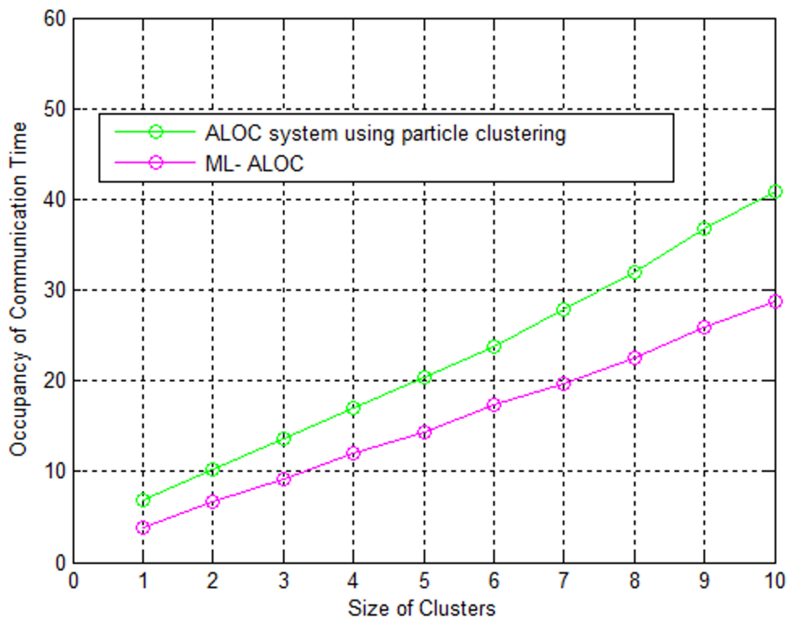


(d)

Figure 13: Error estimation for X position, Y position and yaw angle using ten clusters for (a) and (c) ALOC system using particle clustering (b) and (d) the proposed ML-ALOC method



(a)



(b)

Figure 14: E(a) Communication time per role exchange for each size of the clusters, (b) Occupancy of communication time per role exchange for each size of the clusters

5. Conclusions

Both communication time and estimation accuracy increase with increase in size of clusters in underwater environment is the challenging task to maintain the efficiency during the tracking of the desired path of AUVs in a mission. The goal of the proposed ML-ALOC system is to improve the accuracy of formation by the participating AUVs communicated with compressed positioning data in an underwater environment mission. In the proposed approach, the machine learning based Hierarchical clustering followed by optimal assignment using CNN approach to compress the position data size while transmission and improve the formation of AUVs efficiently under limited communication range. A large number of MATLAB simulations have been performed to verify the effectiveness of the proposed method. The proposed method is compared and found better than particle clustering by minimizing estimation tracking error and data size under limited underwater communication range. Further, the proposed method may be implemented and tested in real time underwater environment.

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