Real-Time Passive Localization of TDOA via Neural Networks

Zewen Wang, Dexiu Hu, Yongjun Zhao, Zhaocheng Hu, and Zhixin Liu

***Abstract*—This letter proposes the use of neural networks to realize the passive localization by signal time difference of arrival (TDOA). In the face of multiple complex targets with radiation sources in a specific area, real-time localization is an urgent problem. In this letter, positions of the known targets from the prior data are obtained and their time difference is calculated, which will be connected as data pairs and input to the neural network trained to obtain a corresponding model. Subsequently, unknown targets can be localized by this network. It is verified that the localization accuracy of the algorithm is reliable and its robustness is higher than that of traditional algorithms. The proposed method also shows that great reduction of operation time depending on the previous network training can complete real-time goals.**

***Index Terms*—Error data, neural network, real-time passive localization, TDOA.**

I. Introduction

PASSIVE localization issue is one of the important technical means in the field of airborne electronic reconnaissance. Different from active localization, passive localization technology has the advantages of high concealment, strong anti-interference, and low cost in the process of achieving the position of the target. Facing the increasingly complex electromagnetic environment [1], it is more and more necessary to study advanced passive localization technology.

In a common multi-station passive localization system, a corresponding localization algorithm is designed according to the extracted intercepted signal parameters and different localization mechanisms in receivers. One or more signal parameters, such as angle of arrival (AOA), time of arrival (TOA), time difference of arrival (TDOA), and frequency difference of arrival (FDOA), are important for multi-station passive localization. Using AOA to achieve positions of targets is an early common technology [2], [3], which mainly relies on the equipment of angle measuring. But its accuracy is not high and the equipment is complicated. Using TDOA, or TDOA and FDOA to achieve positions is more widely used [4]. Under the condition of ensuring that the receivers achieve strict clock synchronization, the accuracy of this method basically meets the localization requirements. In recent years, some more difficult algorithms and technically about localization methods, such as joint TDOA and AOA localization methods [5], [6], have also appeared.

Manuscript received March 26, 2021; revised May 11, 2021 and June 28, 2021; accepted July 9, 2021. Date of publication July 14, 2021; date of current version October 11, 2021. This work was supported by the NSFC of China under grant No. 62071490 and the Natural Science Outstanding Youth Fund of Henan province under grant No. 212300410095. The associate editor coordinating the review of this letter and approving it for publication was S. Sorour. *(Corresponding author: Dexiu Hu.)*

Zewen Wang, Dexiu Hu, Yongjun Zhao, and Zhaocheng Hu are with the Information Engineering University, Zhengzhou 450000, China (e-mail: nj_zewen@outlook.com; paper_hdx@126.com).

Zhixin Liu is with the Institute of Systems Engineering, Academy of Military Sciences, Beijing 100141, China.

Digital Object Identifier 10.1109/LCOMM.2021.3097065

Aiming at the problem of airborne radiation source target localization, especially static or low-speed targets, the localization technology based on time difference is still a hotspot in the research of experts and scholars. Foy used the method of Taylor-series estimation to realize the localization technology [7], [8]. Ho and Xu proposed the use of two-stage weighted least-squares (TSWLS) method, relying on algebraic calculations to obtain an analytical solution for localization directly [4]. In [9], Liu *et al.* proposed an improved TSWLS algorithm, which does not involve nonlinear operations in the second stage, improving the accuracy of localization. In addition, semi-definite relaxation (SDR) localization algorithm was also proposed to solve the problem of calculating the non-convex optimal localization equation recently [10], [11]. After that, Chalise *et al.* proposed an maximum likelihood (ML) optimization problem, and used SDR plus dichotomy to solve it, with the localization performance improving [12]. However, these methods have to solve complex nonlinear localization equations, not fully meeting the battlefield requirements in terms of effectiveness and robustness.

In recent years, artificial neural networks have become a new and popular research direction in the fields of information extraction and data processing. There are also many studies on the use of artificial intelligence technology for passive localization. In the front-end processing of data, complex signal extraction and estimation of TDOA are evolving to artificial intelligence [13], [14]. In the back-end, neural networks are also used for localization algorithm. Zhao used the revised recurrent neural network model for passive localization and found that it obtained high precision position and convergence rate [15]. Pak *et al.* used artificial neural networks for the localization of external radiation sources and compared the localization performance under different data error in TDOA values [16]. Wu *et al.* proposed a pair of mutually inverse networks, using KL (Kullback-Leibler) divergence as a feature, and training the network twice as a localization model [17]. At the same time, other fields such as indoor localization of robot [18] and localization of underwater acoustic [19] have also been studied in similar scenarios. These researches innovatively apply artificial intelligence to localization technology, which not only meets their accuracy, but also improves the effectiveness and robustness.

Inspired by the use of artificial intelligence in localization technology in recent years, this letter mainly studies the real-time localization of radiation source targets in selected airspace using neural networks. First, a localization scene is set up and equation of time difference for the radiation source target in the selected area is established. Then, after the suitable neural network has been trained, real-time localization can be performed. It analyzes and compares the performance of using neural networks and traditional methods to achieve

1558-2558 © 2021 IEEE. Personal use is permitted, but republication/redistribution requires IEEE permission.
See https://www.ieee.org/publications/rights/index.html for more information.

Authorized licensed use limited to: ULAKBIM UASL - MIDDLE EAST TECHNICAL UNIVERSITY. Downloaded on October 11,2024 at 21:15:33 UTC from IEEE Xplore. Restrictions apply.

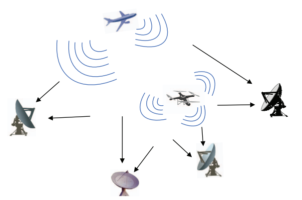

Fig. 1. Real localization scene on the battlefield. Multi-targets transmit signals to multi-station receivers.

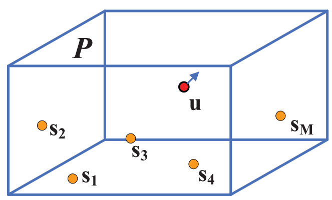

Fig. 2. Schematic diagram of multi-station passive localization scene in selected airspace.

positions of targets. Then the letter calculates the algorithm time consumption and verifies the robustness in experiments. The contribution of this letter is that a suitable network has been constructed, which is used for real-time localization of the radiation source target in the selected area through the preliminary knowledge and training data.

This section mainly introduces the background of neural network used in passive localization system. The second section presents the time difference localization model of radiation source target. The third section mainly describes the localization algorithm of the neural network. The fourth section describes the experimental process and the results. The last section is the summary and the outlook of the work of neural network for localization.

II. The TDOA Model

This letter considers a real-time radiation source localization system. The localization scene is a three-dimensional airspace called $\mathbf{P}$ shown in the Fig. 1 and Fig. 2. The scope of the area $\mathbf{P}$ is $[\alpha_1, \alpha_2] \times [\beta_1, \beta_2] \times [\gamma_1, \gamma_2]$, where $\alpha_1, \alpha_2, \beta_1, \beta_2, \gamma_1, \gamma_2 \in \mathbb{R}$. The true position of the radiation source target is $\mathbf{u}^o = [x^o, y^o, z^o]^T$, where $\mathbf{u} \in \mathbf{P}$. The positions of M receivers in the system are $\mathbf{s}_i{}^o = [x_i{}^o, y_i{}^o, z_i{}^o]^T$, where $i = 1, 2, \cdots, M$, $\mathbf{s}_i^o \in \mathbf{P}$. All receivers of the location information can be defined as $\mathbf{s}^o = \left[\mathbf{s}_1^{oT}, \mathbf{s}_2^{oT}, \cdots, \mathbf{s}_M^{o\,T}\right]^T$.

According to the definition above, the relationship of position between the receivers and the radiation source target can be obtained. Their true distance can be expressed as

$$r_i^o = \|\mathbf{u}^o - \mathbf{s}_i^o\| = \sqrt{(\mathbf{u}^o - \mathbf{s}_i^o)^T (\mathbf{u}^o - \mathbf{s}_i^o)}. \tag{1}$$

Take the receiver $\mathbf{s}_1$ as the reference station, the distance difference between the target and the receiver $\mathbf{s}_1$ and $\mathbf{s}_i$ ($i = 2, \cdots, M$) can be obtained as

$$r_{i1}^o = r_i^o - r_1^o. \tag{2}$$

In a real scene, the measured value of the receiver is TDOA, that is, the time difference t_{i1}^o between the signal of the target reaching from receiver $\mathbf{s}_1$ and $\mathbf{s}_i$ ($i = 2, \cdots, M$). There is only a velocity of electromagnetic wave propagation between it and

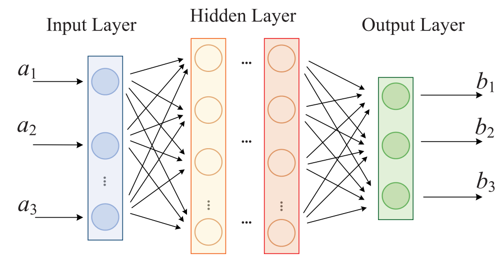

Fig. 3. Simple neural network structure diagram.

r_{i1}^o ($r_{i1}^o = c \cdot t_{i1}^o$). Therefore, in the subsequent discussion of this letter, the distance difference r_{i1}^o is considered to be consistent with the measured TDOA value t_{i1}^o. The measured TDOA from receiver will inevitably have errors, and the distance difference r_{i1}^o will also have errors naturally, which is defined as n_{i1} ($i = 2, \cdots, M$), which satisfies

$$r_{i1} = r_{i1}^o + n_{i1}. \tag{3}$$

Let $\mathbf{r}^o = [r_{21}^o, r_{31}^o, \cdots, r_{M1}^o]^T$ and $\mathbf{r} = [r_{21}, r_{31}, \cdots, r_{M1}]^T$, then $\mathbf{r} = \mathbf{r}^o + \mathbf{n}$, where the measured noise of the receiver is defined as $\mathbf{n} = [n_{21}, n_{31}, \cdots, n_{M1}]^T$. The noisy measurement model is unknown but has covariance matrix as $Q_{\mathbf{n}} = E\left[\mathbf{n}\mathbf{n}^T\right]$.

III. Neural Network Localization Algorithm

A. Neural Networks

Neural network is a special computing model that contains a large number of nodes connected to each other. Each connection line also represents a different weight. It is an important tool for data processing. Neural network has processing capability to nonlinear adaptive information because of its complex structure and adjustable model parameters [20].

The simplest of the neural networks is the feedforward neural network [21], in which each neuron is only connected to the neuron of the previous layer. As shown in the Fig. 3, this neural network has N_1 input values, which are input to the input layer of the network, processed by several hidden layers, and output by the output layer of N_2 nodes. Each hidden layer has several neurons and each unidirectional connecting line contains linear and nonlinear arithmetic relations. Assuming that the two ends of a unidirectional connecting line are a_i and b_j, then their relationship can be expressed as

$$b_j = f(wa_i + \theta), \tag{4}$$

where w represents the weight, θ represents the offset, and $f(\cdot)$ represents the function.

Such a simple neural network structure can infinitely approximate a complex nonlinear equation, that is, fit a mapping relationship from a finite-dimensional space to another [22], [23].

B. Neural Network Localization Algorithm for TDOA

It can be seen from the TDOA model that the localization process is to solve the TDOA equation. In traditional TDOA localization algorithm, as shown in Fig. 4, the equation is established by (1), (2) and solved by a certain

Authorized licensed use limited to: ULAKBIM UASL - MIDDLE EAST TECHNICAL UNIVERSITY. Downloaded on October 11,2024 at 21:15:33 UTC from IEEE Xplore. Restrictions apply.

Fig. 4. Traditional localization flowchart.

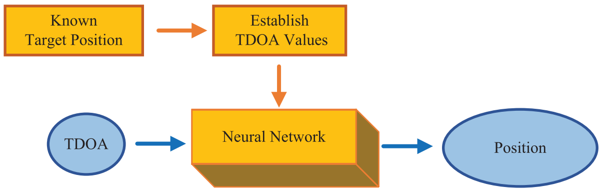

Fig. 5. The localization algorithm flow chart of this letter.

method [4]. This is a non-convex optimization problem, which is often solved by approximation and multiple steps [24]. The above-mentioned network can handle this difficulty well, by fitting a function mapping instead of solving this nonlinear equation.

As shown in the Fig. 5, using neural network to solve the problem of TDOA localization is directly inputting the TDOA data of the receiver into the neural network, and outputting the position data of the target after processing, so as to achieve the position of target. However, the neural network model is not generated naturally. It needs to be obtained through data training in the early stage. Later in the text, the mechanism and localization process using the neural network model will be fully explained.

After obtaining the target signal of the radiation source in the three-dimensional airspace $\mathbf{P}$, the TDOA values will be extracted [25]. The distance difference $\mathbf{r}^o = [r^o_{21}, r^o_{31}, \cdots, r^o_{M1}]^T$ can be obtained to form a set of input and output data pairs $\{\mathbf{r}^o, \mathbf{u}^o\}$ with the real target position $\mathbf{u}^o = [x^o, y^o, z^o]^T$. When the radiation source target has D possibilities in the airspace, there are D data pairs $\{\mathbf{r}^o, \mathbf{u}^o\}_1, \{\mathbf{r}^o, \mathbf{u}^o\}_2, \cdots \{\mathbf{r}^o, \mathbf{u}^o\}_D$. Obviously, the number of input layers of the neural network is determined by the time difference data, that is, $M-1$. The number of output layers is the number of position coordinates, being three. Suppose that the neural network has a total of K hidden layers, and the k^{th} $(k = 1, 2, \cdots K)$ hidden layer has j_k neuron nodes. When a data pair is input, the output of the previous hidden layer is used as the input of the next hidden layer, and the h^{th} $(h = 1, 2 \cdots j_k)$ node output of the k^{th} hidden layer can be obtained as

$$\mathrm{Output}_{kh} = f_{kh}\left(\sum\nolimits_{m=1}^{j_{k-1}} w_{mkh}\mathrm{Output}_{(k-1)m} + \theta_{kh}\right). \tag{5}$$

The position coordinate $\mathbf{u}_{out} = [x_{out}, y_{out}, z_{out}]^T$ of the output layer satisfies the following formula

$$\begin{aligned} x_{out} &= f_{o1}\left(\sum\nolimits_{m=1}^{j_k} w_{o1}\mathrm{Output}_{km} + \theta_{k1}\right) \\ y_{out} &= f_{o2}\left(\sum\nolimits_{m=1}^{j_k} w_{o2}\mathrm{Output}_{km} + \theta_{k2}\right) \\ z_{out} &= f_{o3}\left(\sum\nolimits_{m=1}^{j_k} w_{o3}\mathrm{Output}_{km} + \theta_{k3}\right). \end{aligned} \tag{6}$$

The output of the neural network should approximate the real position coordinates $\mathbf{u}^o = [x^o, y^o, z^o]^T$.From [22], we can get that the hidden layer function of the feedforward neural network can be any measurable function. Therefore, when the nonlinear function $f(\cdot)$ is determined, the network training adjusts the weight and offsets through the value of $\Delta\mathbf{u}$, where $\Delta\mathbf{u} = \mathbf{u}_{out} - \mathbf{u}^o$. The network uses $\Delta\mathbf{u}$ to continuously loop iteratively and obtain the best weights and offsets. Finally, network model $\varphi(\cdot)$ will be fixed.

The training of feedforward network is to transform the nonlinear equation of TDOA into a function mapping. After the training of network is over, real-time localization system can be achieved. When the receivers get new TDOA values, the network can output real-time position results

$$\mathbf{u}_{new} = \varphi(\mathbf{r}_{new}). \tag{7}$$

C. Algorithmic Complexity Comparison

As can be seen from the algorithm above, the use of neural networks is divided into two steps of pre-training and real-time localization. Since the airspace of localization is known in advance, so network training is already done. In the comparison of algorithm complexity, the step of the test is only calculated. In this letter, network model is simplified to calculate the computational complexity. When M TDOA data are get, an appropriate network with k hidden layer above will perform basic operations by $o\left((M-1)j_1 + j_1 j_2 + \cdots + j_{k-1}j_k\right)$ [26].

Calculation complexity of classic algorithm is often based on matrix operation. Taking TSWLS algorithm as an example, the same input takes $o\left(M^3 + b\right)$ operations by matrix operation [10], where b represents the second power and the following polynomials of M.

In summary, the algorithm in this letter relies on the trained network to complete the basic operations from input to output, avoiding the complex matrix operations, like traditional methods, and saving real-time processing time. At the same time, the network can also be input in parallel. Therefore, compared to the TSWLS, the method in this letter can also show advantages in multi-target positioning.

IV. Experiment

A. Experimental Setup

The experimental scenario in this letter is a passive localization problem in a three-dimensional low-altitude battlefield environment. In the scenario, according to the practical application possibilities, the approximate positions of five receivers are set as shown in the following Table I, where receiver 1 is used as the reference station, and the positions of the remaining receivers are set on the order of 1km, which meets the actual application situation. The choice of receiver location is universal and accepted [4], [17].

The airspace $\mathbf{P} = [0, 1]\,(\mathrm{km}) \times [0, 1]\,(\mathrm{km}) \times [0.02, 0.4]\,(\mathrm{km})$ is set as the position traversal range of the entire radiation source target, that is, the target position is basically located 20m to 400m above the receivers.

The position of radiation source target traverses the airspace $\mathbf{P}$. $25 \times 25 \times 20 = 12500$ position data are taken, and TDOA values are calculated by (1) and (2). The 12500 TDOA values and their corresponding real positions are used as data pairs to

Authorized licensed use limited to: ULAKBIM UASL - MIDDLE EAST TECHNICAL UNIVERSITY. Downloaded on October 11,2024 at 21:15:33 UTC from IEEE Xplore. Restrictions apply.

TABLE I

FIVE RECEIVER LOCATIONS

Receiver Label	Location (m)
Receiver 1	(500,500,10)
Receiver 2	(887,583,110)
Receiver 3	(321,767,55)
Receiver 4	(433,238,85)
Receiver 5	(810,229,34)

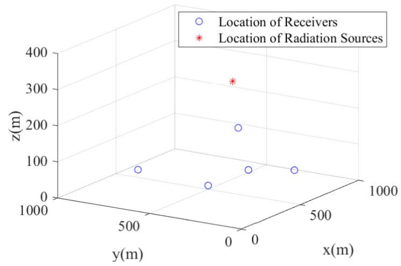

Fig. 6. The experiment set up five different receiver positions and target positions. The positions of receivers are fixed, but the target position is indicative, which can be anywhere in the selected airspace.

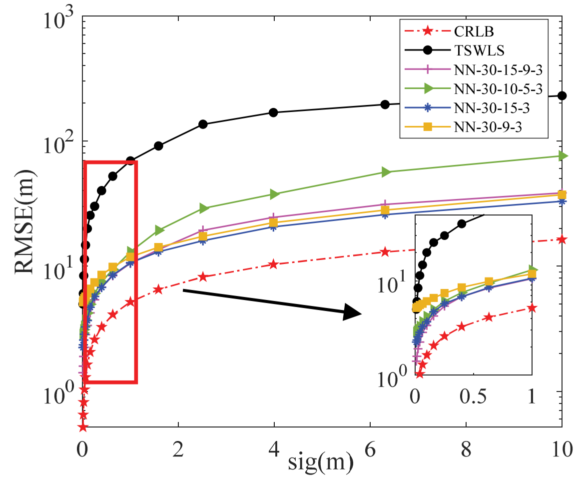

Fig. 7. RMSE for localization using network and TSWLS algorithm is presented under different error conditions. The network structure is constructed in the four forms above.

TABLE II

DIFFERENT STRUCTURED NETWORKS

Network Name	Number of Hidden Layers	Number of Nodes Respectively
NN-30-15-9-3	3	30,15,9
NN-30-10-5-3	3	30,10,5
NN-30-15-3	2	30,15
NN-30-9-3	2	30,9

TABLE III

TIME-CONSUMING FOR LOCALIZATION WITH DIFFERENT METHOD

Method	Consuming time (s)
NN-30-15-9-3	0.381
NN-30-10-5-3	0.375
NN-30-15-3	0.349
NN-30-9-3	0.347
TSWLS	81.775

train the neural network for localization. When a new position in the airspace **P** is selected again, the distance difference of it obtained by (1) and (2) is input into the neural network to obtain the estimated position in time.

B. Localization Estimation Error Comparison

In order to investigate the performance of neural network localization better, this section will calculate the root mean square error (RMSE) of the localization and compare it with the TSWLS algorithm in the case of selecting different TDOA measurement error values for the trained network. In the experiment, the scenes and settings above are still selected, and the measured value error is from -20dB to 10dB. (That means the true error of the distance difference is in the range of 0.01m to 10m.) The results are compared with two algorithms respectively. Different neural network structures, shown in the Table II below, are selected. They are obtained by a large number of training experiments and adjustments to get the best parameters in the early stage. And then they are tested to obtain the localization performance.

As shown in Fig. 7, by comparing the positions results under different errors, it is found that this letter uses a trained neural network to achieve better localization accuracy than the TSWLS algorithm. Comparing the position results of four different networks, it does not absolutely verify which network is the best under all error conditions, which also illustrates the uncertainty of processing in the neural network [27]. But in general, this letter selects some suitable networks, which makes the algorithm of neural network localization better than the traditional algorithm, and approximates the Cramer-Rao lower bound (CRLB) value [4].

In addition to this, the time-consuming of the two algorithms is compared to verify the higher effectiveness of the method in this letter. In the experimental environment of *MATLAB2020b*, the results in the following Table III are obtained. The point that needs to be noted is that the time-consuming of using network positioning algorithms is the calculation of the process time for giving positions with the trained network. When getting the result, using network can reduce the computing time and realize real-time localization.

C. Robustness Comparison

The next experiment continues from the previous part, in order to verify the robustness of the algorithm. From Section IV.B, a best network with name ‘NN-30-15-3’ is selected. The localization error of each target is measured separately. The outliers can be found by comparing the target error data of the continuous plane, which is the unstable point of the position result. The same operation is also performed separately by the traditional algorithm. Under different noise data, the number (12500 points in total) and proportion of unstable points is recorded, shown in the following Table IV.

From the experimental results, there are nearly no instability points by network, while the TSWLS algorithm will have more instability points. In order to display the results better, specially, two experimental result graphs of data are selected from all results (One is the 80m height plane with the

Authorized licensed use limited to: ULAKBIM UASL - MIDDLE EAST TECHNICAL UNIVERSITY. Downloaded on October 11,2024 at 21:15:33 UTC from IEEE Xplore. Restrictions apply.

TABLE IV

PROPORTION OF UNSTABLE POINTS WITH DIFFERENT METHOD

Method/Number (proportion%) of unstable points	Test data noise (dB)				
	-20	-10	0	6	10
TSWLS	44(0.35)	86(0.69)	190(1.52)	217(1.74)	240(1.92)
NN	7(0.06)	10(0.08)	14(0.11)	19(0.15)	24(0.19)

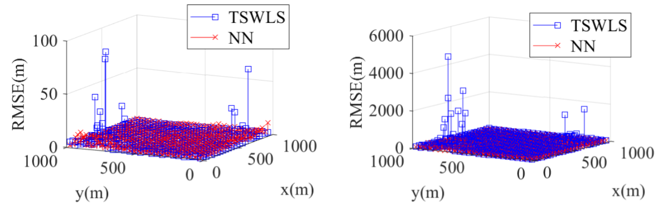

Fig. 8. Robust analysis results of target positions at two different height planes.

measured value error of -20dB, and the other is the 100m height plane with the measured value error of 6dB.), as shown in Fig. 8.

It can be seen that in the positions under the two kinds of noise errors, the traditional TSWLS algorithm has unstable position points. But the neural network used in this letter does not appear obvious unstable points. The main reason is that when using a trained neural network for localization, just simple linear and non-linear operations are used to directly obtain the results. Different from it, the TSWLS algorithm need to solve the least square solution of matrix, which will cause matrix rank missing when solving.

V. CONCLUSION

This letter proposes a solution method of using neural network for target localization in selected areas, which is used in real-time localization of low-altitude radiation source targets. It also analyzes and experimentally verifies the feasibility and effectiveness of the neural network to achieve positions, and the performance is better than the traditional TSWLS algorithm when the measured value contains different noises. In addition, it also proves that the algorithm has fewer time consumption and less unstable points in the experiment. Therefore, the method in this letter has important research significance in reality, especially in real-time localization on the battlefield. When considering the movement of targets and the selection of receiver positions, it is more worth studying in the next work.

REFERENCES

[1] C.-T. Liu, R.-J. Wu, Z.-X. He, X.-F. Zhao, H.-C. Li, and P.-Z. Wang, "Modeling and analyzing interference signal in a complex electromagnetic environment," *EURASIP J. Wireless Commun. Netw.*, vol. 2016, no. 1, pp. 1–9, Dec. 2016.

[2] K. Dogancay, "Bias compensation for the bearings-only pseudolinear target track estimator," *IEEE Trans. Signal Process.*, vol. 54, no. 1, pp. 59–68, Jan. 2006.

[3] H. Wang, S. Kay, and S. Saha, "An importance sampling maximum likelihood direction of arrival estimator," *IEEE Trans. Signal Process.*, vol. 56, no. 10, pp. 5082–5092, Oct. 2008.

[4] K. C. Ho and W. Xu, "An accurate algebraic solution for moving source location using TDOA and FDOA measurements," *IEEE Trans. Signal Process.*, vol. 52, no. 9, pp. 2453–2463, Sep. 2004.

[5] R. Amiri, F. Behnia, and H. Zamani, "Efficient 3-D positioning using time-delay and AOA measurements in MIMO radar systems," *IEEE Commun. Lett.*, vol. 21, no. 12, pp. 2614–2617, Dec. 2017.

[6] Y. Wang and K. C. Ho, "Unified near-field and far-field localization for AOA and hybrid AOA-TDOA positionings," *IEEE Trans. Wireless Commun.*, vol. 17, no. 2, pp. 1242–1254, Feb. 2018.

[7] W. Foy, "Position-location solutions by Taylor-series estimation," *IEEE Trans. Aerosp. Electron. Syst.*, vols. AES-12, no. 2, pp. 187–194, Mar. 1976.

[8] D. Torrieri, "Statistical theory of passive location systems," *IEEE Trans. Aerosp. Electron. Syst.*, vols. AES-20, no. 2, pp. 183–198, Mar. 1984.

[9] Y. Liu, F. Guo, L. Yang, and W. Jiang, "An improved algebraic solution for TDOA localization with sensor position errors," *IEEE Commun. Lett.*, vol. 19, no. 12, pp. 2218–2221, Dec. 2015.

[10] K. C. Ho, X. Lu, and L. Kovavisaruch, "Source localization using TDOA and FDOA measurements in the presence of receiver location errors: Analysis and solution," *IEEE Trans. Signal Process.*, vol. 55, no. 2, pp. 684–696, Feb. 2007.

[11] E. Xu, Z. Ding, and S. Dasgupta, "Source localization in wireless sensor networks from signal time-of-arrival measurements," *IEEE Trans. Signal Process.*, vol. 59, no. 6, pp. 2887–2897, Jun. 2011.

[12] B. K. Chalise, Y. D. Zhang, M. G. Amin, and B. Himed, "Target localization in a multi-static passive radar system through convex optimization," *Signal Process.*, vol. 102, pp. 207–215, Sep. 2014.

[13] H. Su, Q. Bao, and Z. Chen, "Parameter estimation processor for chirp signals based on a complex-valued deep neural network," *IEEE Access*, vol. 7, pp. 176278–176290, 2019.

[14] X. Wang, H. Hua, and Y. Xu, "Pilot-assisted channel estimation and signal detection in uplink multi-user MIMO systems with deep learning," *IEEE Access*, vol. 8, pp. 44936–44946, 2020.

[15] C. Zhao and Y. Zhao, "One recurrent neural networks solution for passive localization," *Neural Process. Lett.*, vol. 49, no. 2, pp. 787–796, Apr. 2019.

[16] S. Pak, B. K. Chalise, and B. Himed, "Target localization in multi-static passive radar systems with artificial neural networks," in *Proc. Int. Radar Conf. (RADAR)*, Sep. 2019, pp. 1–5.

[17] H. Wu, Y. Cheng, and H. Wang, "Data-driven passive localization with non-cooperative radiation sources via mutually inverse networks," *IEEE Commun. Lett.*, vol. 24, no. 4, pp. 792–796, Apr. 2020.

[18] J. Liu, Y. Hu, H. Peng, and A. U. M. Zaki, "Data-driven method using DNN for PD location in substations," *IET Sci., Meas. Technol.*, vol. 14, no. 3, pp. 314–321, May 2020.

[19] M. M. D. Santos, G. G. De Giacomo, P. L. J. Drews, and S. S. C. Botelho, "Matching color aerial images and underwater sonar images using deep learning for underwater localization," *IEEE Robot. Autom. Lett.*, vol. 5, no. 4, pp. 6365–6370, Oct. 2020.

[20] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, pp. 436–444, May 2015.

[21] T. D. Sanger, "Optimal unsupervised learning in a single-layer linear feedforward neural network," *Neural Netw.*, vol. 2, no. 6, pp. 459–473, Jan. 1989.

[22] K. Hornik, M. Stinchcombe, and H. White, "Multilayer feedforward networks are universal approximators," *Neural Netw.*, vol. 2, no. 5, pp. 359–366, 1989.

[23] G. Cybenko, "Approximation by superpositions of a sigmoidal function," *Math. Control, Signals Syst.*, vol. 2, no. 4, pp. 303–314, 1989.

[24] B. T. Poljak, "On the Bertsekas' method for minimization of composite functions," *Lect. Notes Control Inf. Sci.*, vol. 14, no. 1, pp. 178–186, 1979.

[25] A. Yeredor and E. Angel, "Joint TDOA and FDOA estimation: A conditional bound and its use for optimally weighted localization," *IEEE Trans. Signal Process.*, vol. 59, no. 4, pp. 1612–1623, Apr. 2011.

[26] G. Liang, L. Cheng-liang, and G. Lei, "Residual adaptive algorithm applied in intelligent real-time calculation of current RMS value during resistance spot welding," in *Proc. Int. Conf. Neural Netw. Brain*, vol. 3, Oct. 2005, pp. 1800–1806.

[27] M. Mestari, M. Benzirar, N. Saber, and M. Khouil, "Solving nonlinear equality constrained multiobjective optimization problems using neural networks," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 26, no. 10, pp. 2500–2520, Jan. 2015.

Authorized licensed use limited to: ULAKBIM UASL - MIDDLE EAST TECHNICAL UNIVERSITY. Downloaded on October 11,2024 at 21:15:33 UTC from IEEE Xplore. Restrictions apply.