A Novel Device-Free Localization Approach Based on Deep Dictionary Learning

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Abstract. As an emerging technology, device-free localization (DFL) has a wide range of application scenarios in the field of the internet of things. However, most of the existing DFL methods take the mode of learning features from raw data, and then perform to achieve localization using classification, which has inferior localization performance. To improve the localization accuracy, this study proposes an accurate and effective localization technique based on deep dictionary learning with sparse representation (DDL-DFL). The method extracts the in-depth features of the data through multi-layer dictionary learning and stacks the features of each layer for classification. Furthermore, we propose a data augmentation method, which can be applied to scenarios with fewer sensor nodes to increase the data dimension and strengthen the essential features to improve the accuracy of localization. We evaluate the performance of the DDL-DFL algorithm on collected laboratory datasets, and the results are superior to existing localization algorithms. In addition, the DDL-DFL algorithm with data augmentation is conducted on the laboratory datasets with a low dimension of data, and the localization performance has been significantly improved.

Keywords: Device-free localization · Deep dictionary learning · Sparse representation · Classification · Data augmentation

1 Introduction

With the development of the new generation of information technologies, such as the internet of things and cloud computing, the demand for wireless localization is increasing daily. Smart cities, namely urban informatization and intelligence, have become an inevitable trend. Wireless localization has produced a wide range of applications in smart cities, promoting the development of smart cities.

There are already many sophisticated localization methods in the real world, such as GPS [1], ultrasonic localization [2], and radio frequency identification (RFID) localization [3]. The above current localization technology has a good performance in many application fields. However, the application requires the target be equipped with a wireless device, such as a smartphone, which may not be suitable for some scenarios. For example, it cannot usually be assumed that the target is carrying any traceable device in

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an emergency rescue. Therefore, device-free localization (DFL), as an emerging technology [4–7], has a broader application in indoor localization by using wireless devices to detect, track, and locate targets without carrying any additional devices. As shown in Fig. 1(a), in a DFL system, several sensors are arranged around the monitoring area. They are responsible for transmitting and receiving signals in turn, sensing the target's location by the difference of the received signals caused by the target.

Many DFL methods have been proposed, such as fingerprinting, geometric, and Radio Tomographic Imaging (RTI) methods. These techniques are widely based on compressive sensing (CS), and deep learning technology. Youssef et al. [8] first proposed the concept of device-free passive localization. Joey Wilson and Neal Patwari of the University of Utah [9] proposed using radio tomographic imaging for target localization. D. Zhang et al. [10] enhanced the robustness of the localization model by expanding the localization area and introducing more sensor nodes. K. Wu et al. [11] used radio maps constructed from channel state information (CSI) to improve the localization accuracy of single or multiple targets. X. Wang et al. [12] proposed a deep learning indoor localization method based on the CSI matrix. H. Huang et al. [6] proposed a subspace sparse coding-based algorithm for device-free localization. Zhao et al. [13] proposed to treat the location information as a picture and use a convolutional autoencoder algorithm to achieve localization. These pioneering works provided the basis for further DFL research. In addition, many device-free localization methods have been proposed to obtain higher localization accuracy and precision [14–17].

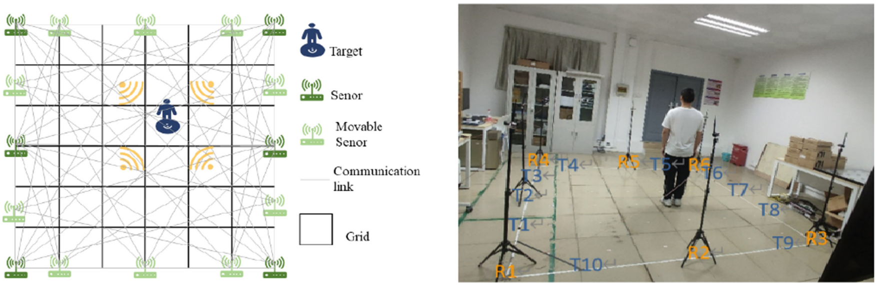
However, most of the above DFL methods are based on learning the original data features, which cannot achieve high localization accuracy. Some methods use CSI data for localization, which is not universally applicable and is only applicable to some wireless devices. Among them, there is also the use of additional sensor nodes to enrich the localization information improving the localization accuracy and increasing the construction cost. To overcome the above drawbacks, this paper proposes a wireless precise device-free localization method based on deep dictionary learning.

The contributions of this paper include the following aspects. First, we propose a wireless device-free localization precise localization method based on deep dictionary learning (DDL-DFL). We obtain a multi-level dictionary through deep dictionary learning, extracting the multi-layer depth features of the data. It is also used as an input to the sparse coding classification model for precise localization. Second, we propose a data augmentation approach that enhances essential features by overlaying data. It makes up for the drawback that the amount of data is not abundant when there are few sensor nodes. Third, to evaluate our algorithm, we use software-defined radio equipment to build a wireless location system to collect laboratory datasets, and conduct experiments on them for localization.

2 Model and Algorithm

2.1 Description of the Localization System

We designate an area of 3×3 square meters inside the laboratory as monitoring area and arrange RF sensors around it, which are responsible for transmitting and receiving signals. Each transmission and reception are simulated as a communication link and all received signal strengths form a matrix. To clearly measure each position within the area, the monitored area is discretized into grids, each grid representing a location. When a target appears at a particular place, due to the blocking and reflection of the target, the communication between the transmitting and receiving sensors will be interfered, and the received signal strength will be attenuated to a certain degree. Therefore, we can locate by studying the attenuation of the signal. For the absence of any target in the monitored area and the presence of targets in different locations, the transceiver correspondence between the sensors is different, and we obtain a different signal matrix. Therefore, when locating an object, we can treat it as a classification problem [6]. The real localization scene built by USRP is shown in Fig. 1 (b).



(a) (b)

Fig. 1. DFL system built in the laboratory. (a) DFL system model in the laboratory; (b) The real localization scene made with USRP.

For the form collected data, we use the received signal strength (RSS), whose processing is more straightforward and universal compared to the literature [11, 12, 18]. In the scenario of Fig. 1, with a total of 36 locations, we set a sensor traversing 10 locations T1–T10 around the monitoring area for transmitting signals. Six sensors R1–R6 are uniformly arranged on both sides of the monitoring area for receiving signals. The received signals are Fourier transformed to select the amplitude information of the first and second harmonics. In this way, we get 12 signal strength information at each transmitting position, for a total of 10 positions, constituting a RSS matrix of size 12×10. To adapt to deep dictionary learning and sparse coding problems, we vectorize the RSS matrix and convert it into a column of size 120×1 for operation. Each location is measured 30 times, and 25 times constitute a matrix of size 120×900 as the training set. Five times the data form a matrix of size 120×180 as the test set.

2.2 Proposed Method

Unlike conventional localization methods based on sparse representation which take the mode of learning features from the original data and then use the classification method to achieve localization, as shown in Fig. 2 (a). The DDL-DFL method performs data augmentation on the training set and test set firstly. Then we obtain a multi-level dictionary through deep dictionary learning, extracting more representative multi-level features in the data. The superimposed multi-layer features are used as training set features and test set features, which are used as localization dictionaries for sparse representation and a localization matrix separately. Finding the data category in the dictionary is most similar to the localization signal with the sparse coding, which is converted to a sparse representation classification problem (SRC) [19]. The localization model is shown in Fig. 2 (b).

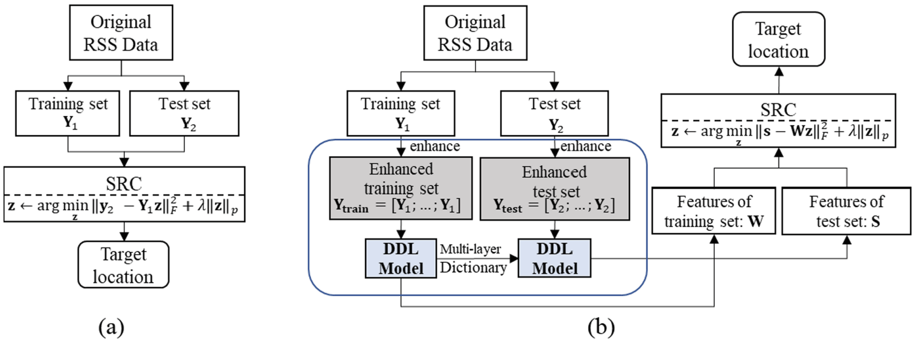


Fig. 2. Graph for localization procedures. (a) Conventional approach. (b) DDL-DFL approach.

Data Augmentation Methods for Localization. For the device-free localization problem based on radio frequency sensors, it is usually necessary to deploy more sensor nodes to enrich the location information to improve the localization accuracy, but it will cost more. This paper proposes a data augmentation method that increases the localization information and strengthens the important features by superimposing the received signal strength in the column direction. We perform the above operations on the training set and the test set separately, then obtain:

$$\boldsymbol{Y}_{train} = [\boldsymbol{Y}_1; \ldots; \boldsymbol{Y}_1], \boldsymbol{Y}_{test} = [\boldsymbol{Y}_2; \ldots; \boldsymbol{Y}_2]. \quad (1)$$

After superposition, the RSS information at different locations is equivalent to reinforcement for strength values with significant disparities (important features), which can promote finding an approximate representation more accurately for the last step.

The feasibility and advantages of the method are demonstrated in the experimental part of the next chapter. The method can still achieve a good localization effect even with slightly fewer sensor nodes.

Deep Dictionary Learning. This paper adopts the deep dictionary model [20], similar to the neural network's layer-by-layer learning method combined with traditional dictionary learning to perform multi-layer dictionary learning. The deep dictionary learning model is as follows:

$$\boldsymbol{Y}_{train} = \boldsymbol{D}_1 \ldots \boldsymbol{D}_l \ldots \boldsymbol{D}_L \boldsymbol{X}_L. \quad (2)$$

Here, $\boldsymbol{Y}_{train} \in \boldsymbol{R}^{q \times r_{train}}$ represents the observation matrix, which is composed of the training set. r_{train} represents the number of signals in $\boldsymbol{Y}_{train}$, q donates the dimension of signals after augmentation, and the dictionary learning has L layers in total. The dictionary of each layer is represented by $\boldsymbol{D}_l \in \boldsymbol{R}^{m_{l-1}\times m_l}$, m_l donates the number of the dictionary atom, l donates the l-th layer, and the representation coefficient is represented by $\boldsymbol{X}_l \in \boldsymbol{R}^{m_l\times r_{train}}$, and $\boldsymbol{Y}_{train}$ is approximately represented by multi-layer dictionaries and representation coefficients.

The input of the first layer is $\boldsymbol{Y}_{train}$, the output is the learned dictionary $\boldsymbol{D}_1$ and the representation coefficient $\boldsymbol{X}_1$. $\boldsymbol{X}_1$ is the input of the next layer, followed by the dictionary learning of the second layer, and so on, until the L-th layer. Take two-layer dictionary learning as an example, as shown in Fig. 3.

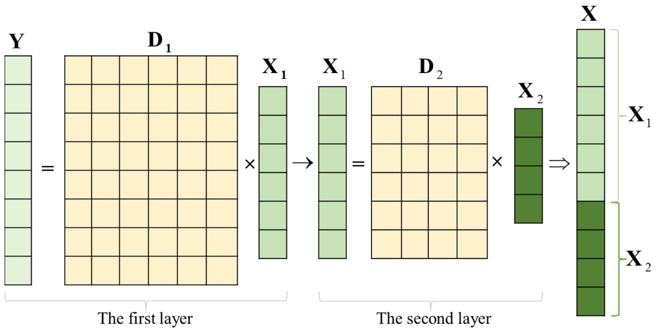


Fig. 3. Deep dictionary learning model diagram.

To solve (2), we transform the above model into the following optimization problem:

$$\min_{\boldsymbol{D}_1,\ldots,\boldsymbol{D}_L,\boldsymbol{X}_1,\ldots,\boldsymbol{X}_L} \|\boldsymbol{Y}_{train} - \boldsymbol{D}_1 \ldots \boldsymbol{D}_L \boldsymbol{X}_L\|_F^2 + \gamma \sum_{l=1}^{L} \|\boldsymbol{X}_l\|_1, \tag{3}$$

where $\|\cdot\|_F^2$ denotes the Frobenius-norm. The left term is the approximation error term, which is used to represent the distance between the observed and estimated signals. The right term is the regularization term, and the ℓ_1-norm is used to promote the sparsity of the coefficients in every layer of representation, and γ is a small constant that balances the error and sparsity term.

Since we integrate the layer-by-layer learning method of deep learning, we can decompose the multivariate problem into L bivariate optimization and solve the problem (4) by alternately updating. For the $l - th$ layer:

$$\boldsymbol{D}_l, \boldsymbol{X}_l \leftarrow \min_{\boldsymbol{D}_l,\boldsymbol{X}_l} \|\boldsymbol{X}_{l-1} - \boldsymbol{D}_l \boldsymbol{X}_l\|_F^2 + \gamma \|\boldsymbol{X}_l\|_1. \tag{4}$$

We solve $\boldsymbol{X}_l$ directly by gradient descent:

$$\boldsymbol{X}_l = (\boldsymbol{D}_l{}^{\boldsymbol{T}} \boldsymbol{D}_l + \gamma \boldsymbol{I})^{-1} \boldsymbol{D}_l{}^{\boldsymbol{T}} \boldsymbol{X}_{l-1}, \tag{5}$$

then update $\boldsymbol{D}_l$:

$$\boldsymbol{D}_l = \boldsymbol{X}_{l-1} \boldsymbol{X}_l{}^{\boldsymbol{T}} (\boldsymbol{X}_l \boldsymbol{X}_l{}^{\boldsymbol{T}})^{-1}. \tag{6}$$

Finally, we get the dictionary $\boldsymbol{D}_1, ..., \boldsymbol{D}_l, ..., \boldsymbol{D}_L$ and representation coefficients $\boldsymbol{X}_1, ..., \boldsymbol{X}_l, ..., \boldsymbol{X}_L$ of each layer. To obtain richer features, we superimpose the representation coefficients obtained from each layer as the training set features $\boldsymbol{W}$:

$$\boldsymbol{W} = [\boldsymbol{X}_1; ...; \boldsymbol{X}_L]. \tag{7}$$

Here $\boldsymbol{W} \in \mathbf{R}^{m \times r_{train}}$, $m = m_1 + ... + m_L$.

The test data directly is decomposed into the representation coefficients through the above trained multi-layer dictionary:

$$\boldsymbol{X}_1^{'}, ..., \boldsymbol{X}_L^{'} \leftarrow \min_{\boldsymbol{X}_1^{'}, ..., \boldsymbol{X}_L^{'}} \|\boldsymbol{Y}_{test} - \boldsymbol{D}_1 ... \boldsymbol{D}_L \boldsymbol{X}_L^{'}\|_F^2 + \gamma \sum_{l=1}^{L} \|\boldsymbol{X}_l^{'}\|_1, \tag{8}$$

where $\boldsymbol{Y}_{test} \in \boldsymbol{R}^{q \times r_{test}}$, $\boldsymbol{X}_l^{'} \in \boldsymbol{R}^{m_l \times r_{test}}$.

Similarly, stacking multiple layers of features constitutes the test set feature $\boldsymbol{S}$:

$$\boldsymbol{S} = \left[\boldsymbol{X}_1^{'}; ...; \boldsymbol{X}_L^{'}\right]. \tag{9}$$

ISTA-Based Localization. With the above two steps, we obtain the training set features matrix $\boldsymbol{W}$ and the test set features matrix $\boldsymbol{S}$, and each column represents a signal. To realize the localization problem, we take $\boldsymbol{W}$ as the localization dictionary and $\boldsymbol{S}$ as the localization matrix. For each localization signal **s** in $\boldsymbol{S}$, since the number of the target position is much smaller than grids, we can represent it approximately linearly sparsely by one or more columns at the same position in the training set features matrix $\boldsymbol{W}$. The labels of the non-zero positions in the sparse representation coefficients correspond to the positions of the targets, i.e., the target is localized by the sparse representation. The classification and localization of the target are achieved using sparse representation, and the schematic diagram is shown in Fig. 4.

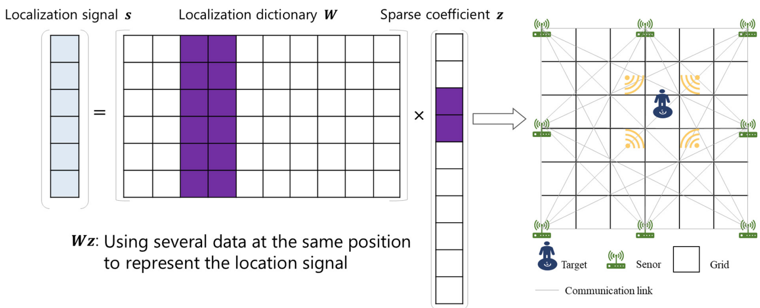


Fig. 4. Schematic diagram of classification and localization based on sparse representation.

Considering that each measured data is in a different scene, then for each localization signal, the classification model is as follows:

$$\boldsymbol{s} = \boldsymbol{W}\boldsymbol{z} + \boldsymbol{n}, \tag{10}$$

where $\boldsymbol{n}$ denotes random noise.

For the device-free localization problem, the more data in the training set, the better, and the more similar signals to the test set can be found, which is more conducive to the realization of classification. Therefore, unlike the previous deep dictionary learning problem, the number of dictionary columns at this stage is greater than the number of rows. The dictionary is overcomplete, and its solution is not unique, so we need to consider the sparsity of $\boldsymbol{z}$. According to the literature [21, 22], we take the ℓ_1-norm as the sparsity constraint, so we can convert problem (10) to solve:

$$\boldsymbol{z} \leftarrow \min_{\boldsymbol{z}} \|\boldsymbol{s} - \boldsymbol{W}\boldsymbol{z}\|_F^2 + \lambda\|\boldsymbol{z}\|_1. \tag{11}$$

Here the first term is the approximate error term, which is used to represent the distance between the localization signal and the estimated signal, the second term is the regularization term, the ℓ_1-norm is used to promote the sparsity of the representation coefficient, and λ is a constant that trades off the error and sparsity terms.

Considering accuracy, speed, and dimensionality, we use the iterative shrinkage thresholding algorithm [23] to optimize problem (11), which is solved as follows:

$$\boldsymbol{z}_{i+1} = \hbar_\theta\left(\frac{1}{C}\boldsymbol{W}^T\boldsymbol{s} + \left(\boldsymbol{I} - \frac{1}{C}\boldsymbol{W}^T\boldsymbol{W}\right)\boldsymbol{z}_i\right), \tag{12}$$

where C is a constant greater than the largest eigenvalue of $\boldsymbol{W}^T\boldsymbol{W}$, $\theta = \lambda/C$ is the shrinkage threshold, $\boldsymbol{I}$ is a unit matrix of the same size as $\boldsymbol{W}^T\boldsymbol{W}$, and $h_\theta(.)$ is the shrinkage function, which is defined:

$$\hbar_\theta(\alpha) = max(|\alpha| - \theta, 0) \bullet sign(\alpha). \tag{13}$$

Here $max(., .)$ represents that the larger of the two items is returned, $sign(.)$ denotes a sign function.

We can also take the OMP algorithm [24] for sparse coding, which performs localization by traversing all columns of localization dictionary and finding the class corresponding to the column with the smallest representation error. In the next chapter, we add DDL and data augmentation to the OMP algorithm, and the localization effect is also well improved.

Through the above method, we can solve the problem (11). Assuming that the number of all categories is P, we let $z_p^* = \sum z_i\,, where\;\; i = arg\, z_i \in class_p$, that is, the coefficients of the $p - th$ class signal are summed, then we can get:

$$\boldsymbol{z}^* = \left\{z_1^*, \ldots, z_p^*, \ldots, z_P^*\right\}. \tag{14}$$

For the single-objective localization problem, the above solution contains only one non-zero term, and the corresponding index is the objective's location. The dual-objective and multi-objective localization problems can be considered based on a combination of the number of non-zero terms and the ordering of the maximum term, and their corresponding indexes are the target locations [6].

Algorithm. The localization algorithm based on deep dictionary learning (DDL-DFL) proposed in this paper is described in Algorithm 1.

Algorithm 1 DDL-DFL

Require: $\boldsymbol{Y}_1 \in \boldsymbol{R}^{n\times r_{train}},\ \boldsymbol{Y}_2 \in \boldsymbol{R}^{n\times r_{test}},\ \boldsymbol{D}_1 \in \boldsymbol{R}^{q\times m_1},\ \boldsymbol{D}_l \in \boldsymbol{R}^{m_{l-1}\times m_l},\ \boldsymbol{D}_L \in \boldsymbol{R}^{m_{L-1}\times m_L},$
$\boldsymbol{W} \in \boldsymbol{R}^{m\times r_{train}},\ \boldsymbol{S} \in \boldsymbol{R}^{m\times r_{test}},\ \gamma,\ \mu,\ C > max\,eig(\boldsymbol{W}^T\boldsymbol{W}),\ \theta = \mu/C, \boldsymbol{I} = \boldsymbol{1}.$

Data augmentation: $\boldsymbol{Y}_{train} = [\boldsymbol{Y_1};\ldots;\boldsymbol{Y_1}], \boldsymbol{Y}_{test} = [\boldsymbol{Y_2};\ldots;\boldsymbol{Y_2}].$

DDL: $\boldsymbol{D}_1,\ldots,\ \boldsymbol{D}_L,\ \boldsymbol{X}_1,\ldots,\ \boldsymbol{X}_L \leftarrow \min_{\boldsymbol{D}_1,\ldots,\boldsymbol{D}_L,\boldsymbol{X}_1,\ldots,\boldsymbol{X}_L} \|\boldsymbol{Y}_{train} - \boldsymbol{D}_1\ldots\ \boldsymbol{D}_L\boldsymbol{X}_L\|_F^2 + \gamma\sum_{l=1}^{L}\|\boldsymbol{X}_l\|_1,$

$\boldsymbol{X}_1',\ldots,\ \boldsymbol{X}_L' \leftarrow \min_{\boldsymbol{X}_1',\ldots,\boldsymbol{X}_L'} \left\|\boldsymbol{Y}_{test} - \boldsymbol{D}_1\ldots\boldsymbol{D}_L\boldsymbol{X}_L'\right\|_F^2 + \gamma\sum_{l=1}^{L}\left\|\boldsymbol{X}_l'\right\|_1.$

$\boldsymbol{W} = [\boldsymbol{X}_1;\ldots;\boldsymbol{X}_L], \boldsymbol{S} = [\boldsymbol{X}_1';\ldots;\boldsymbol{X}_l'].$

Localization: by solving (11).

3 Experimentation and Evaluation

In this section, we evaluate the localization performance of our algorithms using collected laboratory datasets. All algorithms were implemented in MATLAB R2016a and executed on a Windows 64-bit computer with 8 GB RAM and an Intel(R) Core (TM) i5 CPU.

3.1 Experimental Datasets Description

The scenario in our laboratory is six wireless sensors arranged on both sides of a 3 $\times$ 3 m^2 monitoring area for receiving signals and one wireless sensor for transmitting signals, moving through 10 edge locations [16]. We discrete the monitoring area into 36 grids; each grid is with a size of 50 $\times$ 50 cm^2. Sensor nodes are placed at 1.3 m from the ground, targeting 1.75 m of people, and the scene is arranged as shown in Fig. 1.

Each sensor node of the scenario operates in the 2.4 GHz band. Experiments were conducted to collect 30 times data at each location; 25 times data from each location were used as a training set, and five times data were used as a test for localization of the target.

3.2 Evaluation Metrics

To demonstrate the performance of our proposed algorithm, we evaluate it mainly by localization accuracy and average localization error.

The localization accuracy is calculated by: $Accuracy = C_{corret}/C_{total}$, where C_{corret}, C_{total} donates the number of correct localizations in the test data and the total number of test data, respectively.

The average localization error is calculated by the following equation:

$$ALE = \frac{\sum_{c=1}^{C}\sqrt{(x_{predict}^c - x_{true}^c)^2 + (y_{predict}^c - y_{true}^c)^2}}{C}, \tag{15}$$

where $\left(x_{predict}^c, y_{predict}^c\right)$, (x_{true}^c, y_{true}^c) denotes the coordinates of the predicted and true positions of the c-th test data. The C represents the total number of test data.

3.3 Experimental Results

The device-free localization system will inevitably suffer from various influences in real-world scenarios. To better evaluate the performance of our proposed algorithm, we add different levels of Gaussian noise to the localization signal, that is $\boldsymbol{s}^* = \boldsymbol{s} + \boldsymbol{n}$, where $\boldsymbol{n}$ follows a Gaussian distribution. We represent the added noise level by the signal-to-noise ratio (SNR). In the specific implementation, we add SNR levels of 0 dB to 35 dB to the localization data at 5 dB signal-to-noise intervals.

To demonstrate the advantages of our proposed DDL-DFL algorithm, we compare it with original algorithms, including sparse representation classification localization via the OMP algorithm [24], the ISTA algorithm [6]. In the following, the ISTA and OMP algorithm with deep dictionary learning step are referred to as DDL-ISTA and DDL-OMP. In addition, we perform data augmentation for the above four algorithms.

DDL-DFL Localization Algorithm. We put the training set as the input into the two-layer dictionary learning model, the dimensionality of each output layer is [30,20], and γ is set to 0.5. Similarly, the final output of the two-layer representation coefficients is superimposed as the training set features, and the learned dictionary decomposes the test set with two layers of representation coefficients superimposed as the test set features. The training set features constitute the dictionary used for sparse coding, and the test set features are input to the sparse representation classification model.

The performance of our proposed algorithm and the comparison algorithm are measured on the laboratory datasets is shown in Fig. 5. When noise is added to both the training and test sets, we can see by the observation that the DDL-ISTA algorithm has an improvement over the ISTA algorithm in terms of accuracy, and a certain improvement in terms of average localization error. Similarly, for the DDL-OMP algorithm, it performs better than the OMP algorithm in both of metrics. When comparing several algorithms, the DDL-ISTA algorithm effect is the most robust to noise. When noise is added to the training sets, we also observe localization performance of the algorithm after DDL model better than original ways. Experiments on the laboratory datasets measured show that our proposed algorithm DDL-DFL has stronger anti-noise performance compared to original algorithms.

Add Data-Enhanced DDL-DFL Localization Algorithm. Since we have fewer sensor nodes in the laboratory, the data dimension of the datasets is small; the best localization effect may not be achieved. Therefore, we propose a data augmentation method. Before deep dictionary learning extracts deep features, we perform a repeated concatenation of the data to increase the row dimension of the data to strengthen the important features. In the experiment, we superimposed the data five times, and the performance comparison for several algorithms is shown in Fig. 6.

From the results, we find that the effect of adding data augmentation has improved the localization performance of all the above four algorithms by comparing with Fig. 5. Among them, the improvement is even greater for the DDL-DFL algorithm. By experiments on the laboratory datasets, we can conclude that data augmentation is more suitable to the DDL-DFL, and extraction of deep features after data augmentation is not only reduces the data dimension and enhances the real-time for localization, but also improves the localization effect to a certain extent.

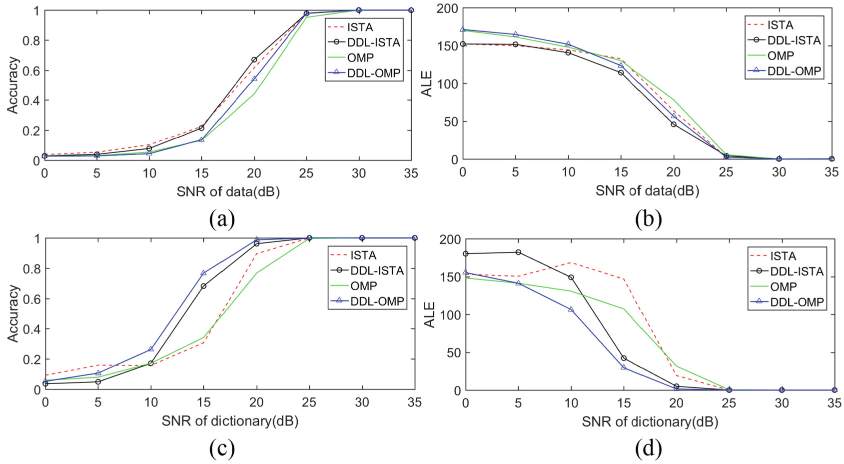


Fig. 5. Localization performance of the proposed DDL-DFL algorithm and the comparison algorithm on the laboratory datasets. (a) Accuracy after adding noise to the training and test data; (b) ALE after adding noise to the training and test data; (c) Accuracy after adding noise to the training data; (d) ALE after adding noise to the training data (unit: cm).

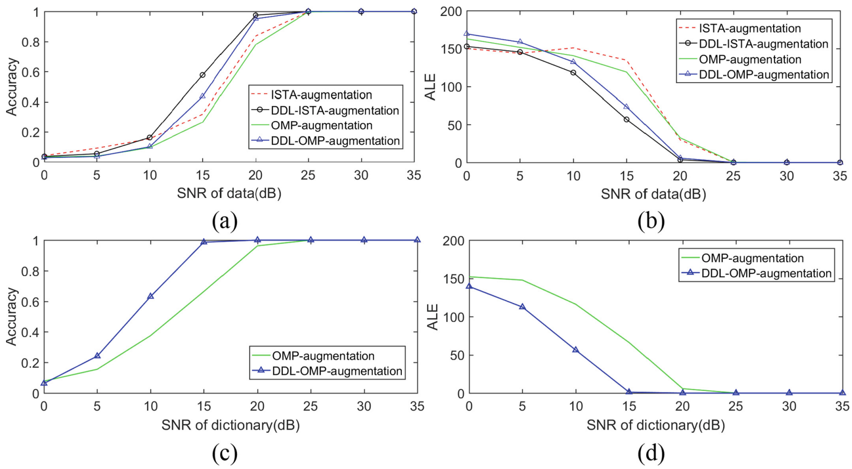


Fig. 6. Localization performance of the proposed add data-enhanced DDL-DFL algorithm and the comparison algorithm on the laboratory datasets. (a) Accuracy after adding noise to the training and test data; (b) ALE after adding noise to the training and test data; (c) Accuracy after adding noise to the training data; (d) ALE after adding noise to the training data (unit: cm).

To explore the performance of our approach, we applied our approaches to the datasets from the University of Utah [9]. In the experiments, we set the process of the DDL part to two layers, with the output dimension of each layer being [392, 196], and the parameter γ is set to 0.5. In the process of the SRC part, the parameters were fine-tuned accordingly, and the data were similarly stacked five times. The experimental results show that our proposed DDL-DFL algorithm achieves an accuracy of about 90% when the training data contains noise at 10 dB SNR level, that is, our proposed method is effective.

4 Conclusion

This study proposes an accurate localization technique based on deep dictionary learning (DDL-DFL). The in-depth features are extracted from the original data through deep dictionary learning, and the representation features of each layer are superimposed as the input of the sparse coding algorithm to realize classification and localization. Furthermore, we propose a data augmentation method applied to the scene with few sensor nodes to increase the data dimension. In this way, we can strengthen the essential features and further improve the algorithm. Experiments on real-world datasets show that the proposed method can achieve 100% localization accuracy in case of lower SNR and has certain anti-noise performance. The results are better than existing localization algorithms.

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