IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received September 18, 2019, accepted October 5, 2019, date of publication October 8, 2019, date of current version October 18, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2946298

WeUp: Wireless User Perception Based on Dimensional Reduction and Semi-Supervised Clustering

KAIXUAN ZHANG[1], (Student Member, IEEE), WENJUAN SHI[1,2], (Member, IEEE), JUN ZENG[1], (Student Member, IEEE), GUANGHUI FAN[1], (Student Member, IEEE), YU WANG[1], (Student Member, IEEE), AND GUAN GUI[1], (Senior Member, IEEE)

[1]College of Telecommunications and Information Engineering, Nanjing University of Posts and Telecommunications, Nanjing 210003, China
[2]School of New Energy and Electronic Engineering, Yancheng Teachers University, Yancheng 224007, China

Corresponding author: Guan Gui (guiguan@njupt.edu.cn)

This work was supported in part by the Jiangsu Specially Appointed Professor Program under Grant RK002STP16001, in part by the Program for Jiangsu Six Top Talent under Grant XYDXX-010, in part by the Program for High-Level Entrepreneurial and Innovative Talents Introduction under Grant CZ0010617002, and in part by the 1311 Talent Plan of Nanjing University of Posts and Telecommunications.

ABSTRACT Wireless user perception (WeUP) is considered one of the most important factors in designing next-generation wireless communications systems. The recognition of WeUP involves lots of labor cost up to now. In order to solve this problem, this paper proposes an accuracy recognition algorithm for WeUP based on dimensional reduction and semi-supervised clustering. Usually, the WeUP is highly reflected in the key quality indicator (KQI). we build up a database of KQI including more than 1000 cells to train a deep belief autoencoder (DBA) for dimensional reduction (DR). Then we feed the historical unlabeled and manual-labeled negative data set after dimensional reduction into semi-supervised clustering model. After that, we find out a recognition range, which is the most similar to manual-labeled objects with unsatisfied WeUP. Simulation results show that our proposed method achieves an accurate recognition of unsatisfied WeUP over 93%.The study indicates that dimensional reduction and semi-supervised machine learning method is effective in recognizing unsatisfied WeUP in wireless networks.

INDEX TERMS Wireless user perception (WeUP), dimensional reduction (DR), semi-supervised clustering, deep belief autoencoder (DBA).

I. INTRODUCTION

With the development of wireless communications [1]–[14] and internet of things (IoT) [15]–[18], wireless users often require good experience on wireless user perception (WeUP). In parallel, WeUP is gaining interest, which aims at providing good and stable services to users. However, unsatisfied WeUP appears in some cells, which cannot be filtered effectively with traditional methods by setting rules. The research motivation comes principally from complaints of users. The direct measurement of WeUP involves human participation and it requires a lot of time and effort. Two methods are proposed to improve quality of experience (QoE) [19], [20]. These methods focus on solving problems from a theoretical perspective, which ignores the practical problems in real system [21], [22]. However, WeUP is highly relevant to the practical data.

Key quality indicator (KQI) data reflects the quality of WeUP. It consists of 14 features. For each cell, there are 8 rows of KQI data. Every object features 8 rows and 14 columns. In order to realize visualization and low computational complexity, dimensional reduction (DR) [23] is considered one of effective methods. M. Abdulhussain et al. proposed a principal component analysis (PCA) method to achieve dimensional reduction of text features [24]. Singular value decomposition (SVD) is a typical methodology to perform PCA. However, PCA based methods cannot explain the complex polynomial relationship between features. In [25], dimensional reduction is applied to extract features from Hyper Spectral Nonnegative data. Shylaja *et al.* [26] use linear discriminant analysis (LDA) and SVD to improve the

The associate editor coordinating the review of this manuscript and approving it for publication was Min Jia.

efficiency of face recognition task. Existing DR algorithms perform well in linear relationship between features and face recognition. However, when these DR algorithms are used in the KQI data, the information loss is high and the recognition accuracy is low.

Supervised based machine learning methods are proposed to perform classification and recognition in many applications [27]–[33]. For example, R. Kajale et al. propose a supervised machine learning method using classifiers and transferring the data to excel sheet is used for intelligent character recognition [33]. Recently, unsupervised machine learning methods are used for recognition and classification of text or images. However, these methods usually come with uncertainty because the data sets are unlabeled. Semi-supervised learning has been studied for a long history, which aims to classify a massive number of unlabeled objects given the existence of only a few labeled objects. Recently, many state-of-the-art semi-supervised methods are developed in wireless communications [34]–[46].

Motivated by these previous research, in this paper, we propose an effective WeUP system via dimensional reduction and semi-supervised clustering. This system is distinguished from existing methods. We design a neural network for dimensional reduction in this particular application scenario. The semi-supervised clustering method works based on the data sets including partial data known. More precisely, we build up a data set of KQI from more than 1000 cells to train a deep belief autoencoder (DBA) for DR. Here DBA is applied to reduce the data dimension since it has low MSE in two dimensions [47]. DBA not only avoids the disadvantage of linear algorithms, but also improves the recognition accuracy. Then we divide history KQI data into different classes, and find out the most similar class to objects with unsatisfied WeUP by semi-supervised clustering method [48]. We define a recognition range according to the density of objects. Finally, we need to observe whether the manual-labeled objects fall into the recognition range to test recognition accuracy. The recognition accuracy is 93.7% by dimensional reduction and semi-supervised clustering.

The rest of this paper is organized as follows. Section II gives the system model. Section III introduces the data preprocessing. Section IV gives the introduction of dimensional reduction algorithm. The semi-supervised clustering algorithm is introduced in Section V. Section VI gives the performance evaluation of the proposed algorithm. Section VII summarizes our work.

II. SYSTEM MODEL

Figure 1 gives the flowchart of our proposed algorithm model, which consists of data preprocessing, dimensional reduction and semi-supervised clustering. Firstly, when the KQI data is entered into this model, it will be preprocessed into a vector. In the part of dimensional reduction (DR). we propose a DBA network to realize DR of the KQI data. The DBA works well with low information loss, which saves the non-linear characteristics of the KQI data. A semi-supervised clustering method is proposed to create an algorithm model for recognition of WeUP. The object after DR is located and recognized whether it belongs to the recognition range, which is given in this model. Finally, the algorithm model outputs the result of WeUP for this object.

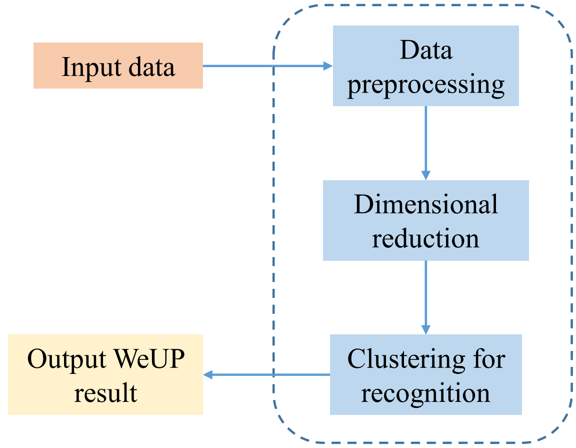


FIGURE 1. The framework of the recognition system.

III. DATA PREPROCESSING

A. DATA DESCRIPTION

In this paper, the data sets are obtained from wireless quality monitoring terminals. The relationship between F_i ($i = 1, 2, \ldots, 14$) and 14 features are given in Table 1. Taking Cell 1 as an example, the KQI data of Cell 1 is given in Table 2. As shown in Table 2, each row shows 14 features at different time. In total, there are more than 8000 cells in a data set. For cells in Table 2, the quality of WeUP is unknown. Table 3 gives another example of cells with unsatisfied WeUP. We consider this table as a negative data set. There are more than 2000 cells in this data set.

TABLE 1. The relationship between F_i and 14 indicators.

F_i	Features Name
F_1	Page response success rate (%)
F_2	Page response delay (ms)
F_3	Page display success rate (%)
F_4	Page display delay (ms)
F_5	Page download rate (kbps)
F_6	Video play success rate (%)
F_7	Video pause time per minute
F_8	Pause time ratio
F_9	Cache time delay (ms)
F_{10}	Stream media rate (kbps)
F_{11}	Instant communication response success rate (%)
F_{12}	Instant communication response delay (%)
F_{13}	Mobile game response success rate (%)
F_{14}	Mobile game response delay (ms)

B. DATA PREPROCESSING

Data preprocessing refers to a set of activities that is done to make raw data suitable for further processing in dimensional

TABLE 2. The KQI data of one cell.

Cell Name	Time	F_1	F_2	$\cdots$	F_{13}	F_{14}
Cell 1	08:00	98.11	36	$\cdots$	100.00	41.00
Cell 1	09:00	98.90	20	$\cdots$	100.00	37.64
Cell 1	10:00	100.00	35	$\cdots$	89.33	53.54
Cell 1	18:00	99.60	28	$\cdots$	66.65	24.00
Cell 1	19:00	100.00	98	$\cdots$	88.89	29.00
Cell 1	20:00	98.67	154	$\cdots$	92.31	149.40
Cell 1	21:00	99.14	56	$\cdots$	100.00	1839.84
Cell 1	22:00	96.55	58	$\cdots$	85.55	25.92

TABLE 3. One cell with manual-labeled WeUP.

Cell Name	Time	F_1	F_2	$\cdots$	F_{13}	F_{14}
Bad_cell 1	08:00	82.30	245	$\cdots$	88.00	99.50
Bad_cell 1	09:00	75.45	210	$\cdots$	79.45	88.56
Bad_cell 1	10:00	80.56	158	$\cdots$	81.22	102.12
Bad_cell 1	18:00	77.58	105	$\cdots$	69.75	100.53
Bad_cell 1	19:00	68.45	116	$\cdots$	80.25	77.58
Bad_cell 1	20:00	79.63	100	$\cdots$	82.35	125.56
Bad_cell 1	21:00	66.53	123	$\cdots$	80.44	500.58
Bad_cell 1	22:00	82.58	188	$\cdots$	79.53	425.36

reduction and clustering. Data preprocessing is one of the first and critical steps for data mining and data analysis. In this paper, the data preprocessing contains of data cleaning, normalization and vectorization. Data cleaning is necessary for further processing due to a lot of missing value of the raw data. We delete the data of cells with a large number of missing values and fill missing value with median for the rest data. Normalization is to eliminate the dimensional influence among different indicators. In this paper, we opt for Min-Max normalization algorithm to convert the raw data to the range between 0 and 1. The Min-Max normalization is defined as

$$x^* = (x - x_{min})/(x_{max} - x_{min}) \tag{1}$$

where x_{min} and x_{max} represent the minimum and maximum value in a column respectively. Table 4 shows the result of Table 1 after normalization.

TABLE 4. The result of Table 1 after normalization.

Cell Name	Time	F_1	F_2	$\cdots$	F_{13}	F_{14}
Cell 1	08:00	0.452	0.119	$\cdots$	1.000	0.009
Cell 1	09:00	0.681	0	$\cdots$	1.000	0.008
Cell 1	10:00	1.000	0.112	$\cdots$	0.680	0.016
Cell 1	18:00	0.884	0.060	$\cdots$	0	0
Cell 1	19:00	1.000	0.582	$\cdots$	0.667	0.003
Cell 1	20:00	0.614	1.000	$\cdots$	0.769	0.069
Cell 1	21:00	0.751	0.269	$\cdots$	1.000	1.000
Cell 1	22:00	0	0.284	$\cdots$	0.567	0.001

The vectorization plays an important role in the algorithm model. The process is illustrated in Figure 2 which the raw data is generated in the form of a matrix. We try to reshape the matrix to a vector with the data characteristics unchanged.

IV. DIMENSIONAL REDUCTION

As we can see in the aforementioned data description, the dimension of the data sets is very high, which causes

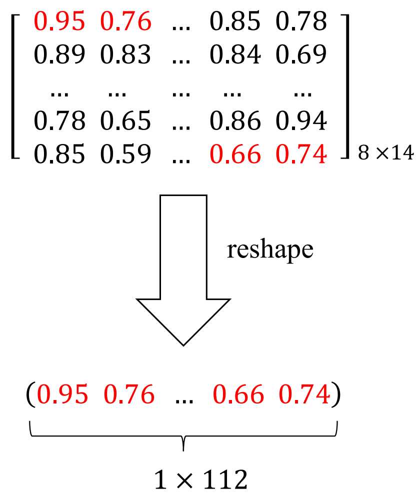


FIGURE 2. A data matrix of one sample with 8 × 14 is converted into a vector with 1 × 112.

invisibility and high computational complexity. Specifically, it is very hard to observe the characteristics of KQI data in high dimensions. Thus, it is impossible to find out the similarity between the unknown objects and those with unsatisfied WeUP. Hence, it is necessary to project the data from high dimension into two dimensions (2D) so that we can see the distribution and characteristics of the KQI data in 2D. Considering the nonlinear correlation among KQI features, we create a DBA which is inspired by deep belief network (DBN) to reduce the dimension. Both DBA and DBN consist of a set of Restricted Boltzmann Machines (RBMs) and the network training is the same.The distinguish of DBA is that the number of neurons in each layer is determined by our experimental result. and the number of neurons in core layer is designed as the number of dimensions. DBA consists of the encoder module and the decoder module. The structure of DBA is shown in Figure 3.

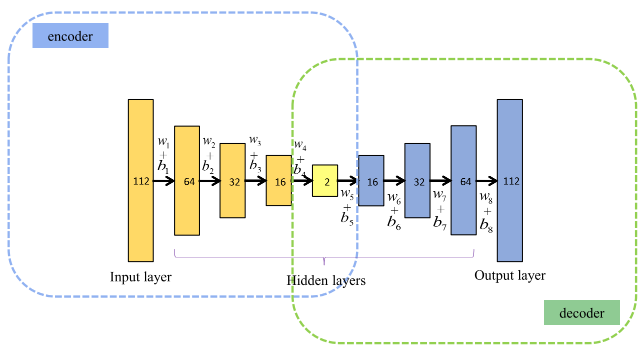


FIGURE 3. The number in each layer represents the number of neurons. The adjacent layers are fully connected to each other. The *W* and *b* between adjacent layers are trained. After the DBA model training is completed, we use the core layer in the DBA as feature.

Encoder: In Figure 3, the input vectors ($x_i \in R^{112}$) are compressed into 64 numbers of neurons, which constitute the first hidden layer. The activation of the i-th neuron in this hidden layer is given by:

$$h_i = s\left(\Sigma_{j=1}^{112} w_{ij}^{input} x_j + b_i^{input}\right) \tag{2}$$

where x is the input vector, W represents the encoder weight matrix with size 64 × 112 and b is a bias vector of dimension 64. The Sigmoid function $s(*)$ is used as the activation function and it is defined by:

$$s(x) = 1/\left(1 + e^{(-x)}\right) \tag{3}$$

Through the first hidden layer, the input vector is encoded to a dimension 64 vector. The other hidden layers work like this until the input vector is encoded to 2D.

Decoder: From the last hidden layer to output layer, the $h_i \in R^{64}$ is decoded back to the original input space R^{112}. The mapping function is given by:

$$x_i' = s\left(\sum_{j=1}^{64} w_{ij}^{hidden} h_j + b_i^{hidden}\right) \tag{4}$$

We optimize the DBA to minimize the cost function

$$C = \frac{1}{n}\sum_{i=1}^{n} \left\|x_i' - x_i\right\|^2 \tag{5}$$

where n denotes the number of objects. X' and X represent the output and input vector, respectively. $\|x_i' - x_i\|$ is the ℓ_2-norm of vector $(x_i' - x_i)$ and the ℓ_2-norm is defined as

$$\|v\|^2 = \sum_{i=1}^{n} |v_i|^2 \tag{6}$$

The change in a weight is given by

$$w_i' = w_i - \alpha\frac{\partial C}{\partial w_i} \tag{7}$$

where w_i' is the weight changed. α is a learning rate which equals to 0.1. And the $\frac{\partial C}{\partial w_i}$ is the gradient of w_i computed by back propagation (BP) algorithm [50]. In the same way, the change in a deviation is given by

$$b_i' = b_i - \alpha\frac{\partial C}{\partial b_i} \tag{8}$$

where b_i' is the changed deviation, the $\frac{\partial C}{\partial b_i}$ is the gradient of b_i computed by BP algorithm. The DBA model trained is saved to reduce the dimension of KQI data, which saves the non-linear characteristics of the original data and works with low information loss. When a new sample is entered into DBA, the encoder module encode this sample to two dimensions, which is the output of the core layer.

V. SEMI-SUPERVISED CLUSTERING ALGORITHM

After dimensional reduction, we need to input the data set into the clustering module to create a recognition range. Considering that the data set includes partial labeled samples, we design a semi-supervised clustering algorithm to recognize the quality of WeUP.

K-means clustering algorithm is one of the most popular algorithms in unsupervised clustering [51]. Suppose that we are given a data set $X = (x_1, \ldots, x_N)$, where $x_n \in R^d$. The M-clustering problem aims at partitioning this data set into M disjoint clusters $\{C_1, \ldots, C_M\}$. Although K-means clustering algorithm owns simple principle and usually works with good results, the results usually come with uncertainty. In this paper, we propose a semi-supervised clustering algorithm based on k-means clustering algorithm. More precisely, a number of unlabeled data is grouped into k classes and output k centroids. The K value is determined by our experimental result shown in section VI. The rationale of this step is similar to k-means clustering. Then we calculate the distances between each sample labeled as negative and k centroids, then partition this negative data set into k classes according to the least distance judgement. We viewed the class containing of more than 90% negative samples as the negative class and set a recognition range in this class according to the density of negative samples. Once we set the recognition range, we just need to calculate whether a new sample belongs to this range to recognize the quality of WeUP. The proposed semi-supervised clustering algorithm can be described in the Algorithm 1. The structure of the proposed algorithm is presented in Figure 4.

Algorithm 1 Semi-Supervised Clustering Algorithm.

Problem: Find out the accuracy recognition range.
1 Input: Unlabeled data set after dimensional reduction.
2 Initialization: k centroids.
3 While objects move, do
Compute distances between each object and k centroids, then partition this data set into k disjoint subsets;
Compute the centroids again in each subset;
4 Input: negative data set;
5 Compute distances between each object in the negative data set and k centroids, then partition this data set into the k classes;
6 Set a recognition range according to the density of negative objects;
7 Output the recognition range.

Various distance functions are used to measure the similarity among the objects. The distance function is measured by Euclidean distance [52]. The Euclidean distance between vector $X = (x_1, x_2, \ldots, x_n)$ and $Y = (y_1, y_2, \ldots, y_n)$ can be defined by

$$dist(X, Y) = \sqrt{\sum_{k=1}^{n}(x_k - y_k)^2} \tag{9}$$

As shown in Figure 5, both unlabeled data set and negative data set are entered into the clustering model after DR. Each point in this figure presents an object. The purple and yellow points constitute the unlabeled data set. The negative data set is presented as red points. For precise recognition of unsatisfied WeUP, it is required to find the most similar objects to the negative data. A circle with an appropriate radius is created as the recognition range. Hence, we just need to observe if an

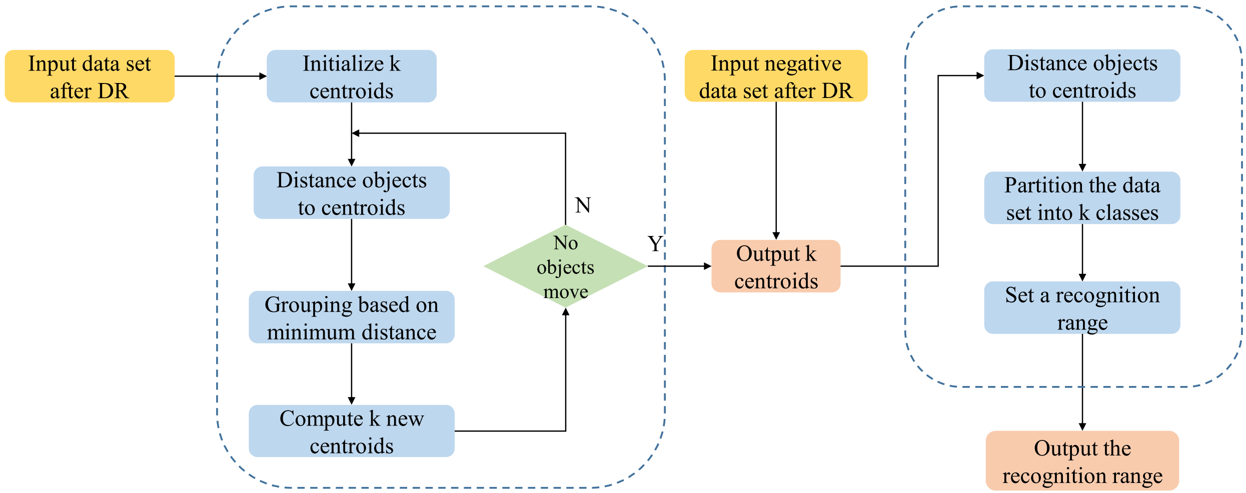


FIGURE 4. The structure of semi-supervised clustering.

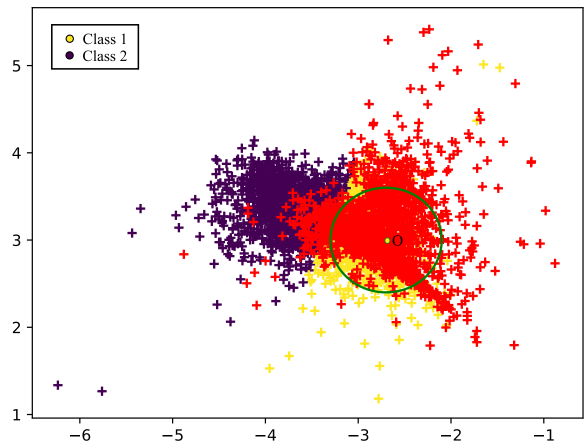


FIGURE 5. The result of semi-supervised clustering algorithm.

TABLE 5. The test data set.

label	Cell Name	Time	F_1	F_2	$\cdots$	F_{13}	F_{14}
0	Cell 1	08:00	99.11	35	$\cdots$	99.54	56
	Cell 1	09:00	97.9	27	$\cdots$	98.36	53
	Cell 1	10:00	99.84	37	$\cdots$	95.33	63
	Cell 1	18:00	99.64	78	$\cdots$	96.32	47
	Cell 1	19:00	96.51	93	$\cdots$	98.89	58
	Cell 1	20:00	97.67	45	$\cdots$	97.31	83
	Cell 1	21:00	99.14	63	$\cdots$	99.56	49
	Cell 1	22:00	96.45	46	$\cdots$	96.55	38
1	Cell 2	08:00	79.11	136	$\cdots$	81.26	385
	Cell 2	09:00	74.90	120	$\cdots$	73.65	1145
	Cell 2	10:00	68.32	155	$\cdots$	81.33	568
	Cell 2	18:00	88.53	128	$\cdots$	86.65	486
	Cell 2	19:00	85.36	198	$\cdots$	78.89	785
	Cell 2	20:00	78.67	164	$\cdots$	82.31	423
	Cell 2	21:00	79.14	156	$\cdots$	83.52	1254
	Cell 2	22:00	82.55	128	$\cdots$	85.55	452

unlabeled object fall into this range to recognize its label of WeUP.

VI. PERFORMANCE EVALUATION OF THE PROPOSED ALGORITHM

A. INTRODUCTION OF THE TEST DATA SET

In order to test the recognition accuracy of this proposed algorithm model, we generate a data set of cells with known

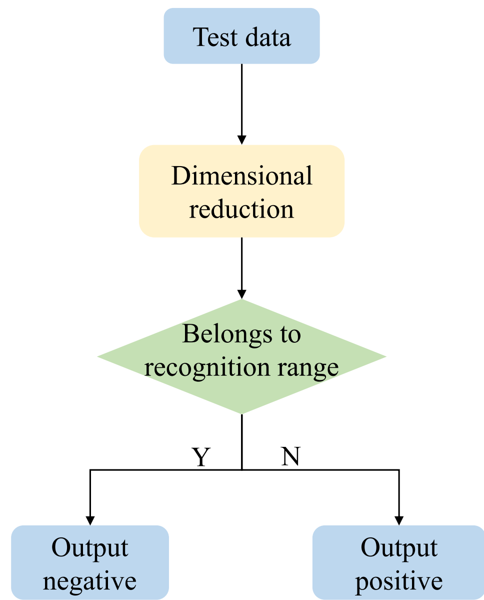


FIGURE 6. The test flowchart of recognition accuracy.

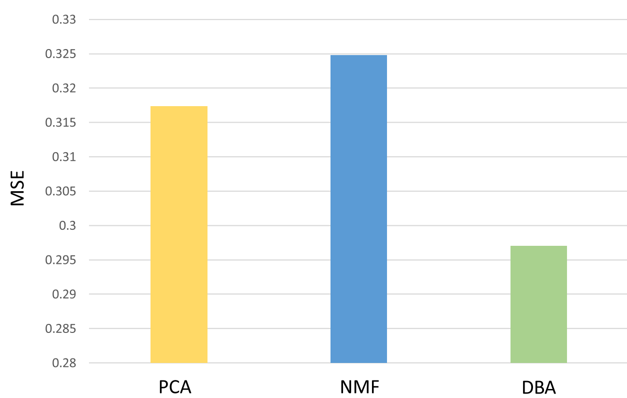
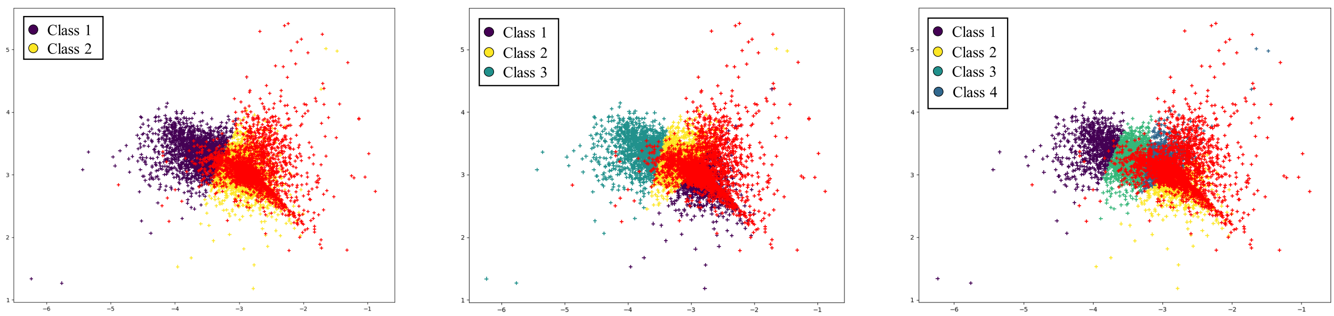


FIGURE 7. The comparison of information loss of three DR algorithms.

WeUP as test data. Taking two cells from the data set as an example in Table 5, we label cells with good KQI data with 0 and label those with poor KQI data with 1. The objects



(a). K=2 (b). K=3 (c). K=4

FIGURE 8. The comparison of semi-supervised clustering algorithm with different k.

TABLE 6. Comparison of recognition accuracy among different dimensions.

Dimension of input	Dimension of core layer	Number of hidden layers	Recognition accuracy
112	2	7	**93.70%**
112	10	7	**68.53%**
112	50	7	**61.60%**
112	100	7	**56.30%**

TABLE 7. Comparison of recognition accuracy among different hidden layers.

Dimension of input	Dimension of core layer	Number of hidden layers	Recognition accuracy
112	2	3	**76.37%**
112	2	5	**66.17%**
112	2	7	**93.70%**
112	2	9	**86.41%**

labeled 0 are positive and the objects labeled 1 are negative. The flowchart of the test is presented in Figure 6.

B. PERFORMANCE COMPARISON

In order to demonstrate the performance of our proposed algorithm, in this section, we compare the performance of the proposed DBA with two popular DR algorithms including PCA [53] and Non-negative matrix factorization (NMF) [54] in terms of information loss. PCA is used widely due to its simplicity. PCA can be perceived as an unsupervised statistical linear dimension reduction scheme. PCA is a conventional method to find projection direction along which the total mean squared error is minimum. NMF is a group of algorithms in multivariate analysis and linear algebra where a matrix V is factorized into two matrices W and H, with the property that all three matrices have no negative elements. This non-negativity makes the resulting matrices easier to inspect. NMF can be widely used in image analysis, text mining and speech processing. We use PCA, NMF and the proposed DBA to perform dimensional reduction on the KQI data. Different algorithm comes with different mean-square error (MSE), which refers to information loss. The information loss of the three algorithms is shown in Figure 7. We can observe that the proposed DBA can achieve the best performance due to its minimum MSE. Therefore, the proposed DBA is the most suitable algorithm for DR of KQI data among the three algorithms.

Different k value leads to different recognition range. The comparison of results with different k value in semi-supervised clustering algorithm are shown in Figure 8. In the three subplots, red points represent negative objects. We need find the class which is highly coincident with red points. Obviously, class 2 is overlapped with more than 90% of red points in Figure 8(a). We can consider class 2 as the negative class. However, we cannot find the most suitable class when k equals 3 or 4 as shown in Figures 8(b) and 8(c). Finally, k value is selected as 2. When we find out the best negative class, we set the recognition range in this class.

Considering the KQI data might have different characteristics in different lower dimensional space, the recognition accuracy is highly related to the final dimension of KQI data. In this section, we try to change the number of neurons of the core layer in DBA, which means the data is converted into different dimensions to compare the recognition accuracy. The results are shown in Table 6. As we can see from the table, the recognition accuracy increases with the decrease of the number of neurons in the core layer. The best recognition accuracy 93.7% is achieved when the input data is converted to two-dimensional space.

Compared to other dimensional reduction algorithms, another advantage of DBA is that we can adjust the number of hidden layers according to the performance of the whole system. We conduct experiments based on different hidden layers, and the experimental results are shown in Table 7.

Considering the symmetry of neural network, we opt for 3, 5, 7, 9 as the number of hidden layers. When the number of hidden layers is more than 9, the performance decreases sharply. We can see from Table 7, when the number of hidden layers equals 7, the recognition accuracy is highest.

VII. CONCLUSION

This paper has proposed an effective method to recognize cells with unsatisfied WeUP. The whole algorithm model was created based on a large number of historical data with machine learning methods. The model can be depicted by three parts including data preprocessing, dimensional reduction and semi-supervised clustering. For higher recognition accuracy, many parameters have been adjusted in this model and finally the recognition accuracy can be increased to 93.7%. The operators can formulate solutions to solve the unsatisfied WeUP according to the precise recognition. However, the recognition accuracy needs to be further improved. In the further research, the relationship between KQI and KPI should be analyzed in order to find out the basis reasons of unsatisfied WeUP.

ACKNOWLEDGMENT

The authors would like to express their thanks to the BOCO Inter-Telecom for their KQI data.

REFERENCES

[1] Z. Na, Y. Wang, X. Li, J. Xia, X. Liu, and M. Xiong, "Subcarrier allocation based simultaneous wireless information and power transfer algorithm in 5G cooperative OFDM communication systems," *Phys. Commun.*, vol. 29, pp. 164–170, Aug. 2018.

[2] M. Jia, X. Gu, Q. Guo, W. Xiang, and N. Zhang, "Broadband hybrid satellite-terrestrial communication systems based on cognitive radio toward 5G," *IEEE Wireless Commun.*, vol. 23, no. 6, pp. 96–106, Dec. 2016.

[3] X. Liu, X. Zhang, M. Jia, L. Fan, W. Lu, and X. Zhai, "5G-based green broadband communication system design with simultaneous wireless information and power transfer," *Phys. Commun.*, vol. 28, pp. 130–137, Jun. 2018.

[4] M. Liu, T. Song, and G. Gui, "Deep cognitive perspective: Resource allocation for NOMA based heterogeneous IoT with imperfect SIC," *IEEE Internet Things J.*, vol. 6, no. 2, pp. 2885–2894, Apr. 2019.

[5] G. Gui, H. Sari, and E. Biglieri, "A new definition of fairness for non-orthogonal multiple access," *IEEE Commun. Lett.*, vol. 23, no. 7, pp. 1267–1271, May 2019.

[6] M. Wei, S. Sezginer, G. Gui, and H. Sari, "Bridging spatial modulation with spatial multiplexing: Frequency-domain ESM," *IEEE J. Sel. Topics Signal Process.*, to be published. doi: 10.1109/JSTSP.2019.2913131.

[7] Z. Zhou, M. Dong, K. Ota, G. Wang, and L. T. Yang, "Energy-efficient resource allocation for D2D communications underlaying cloud-RAN-based LTE-A networks," *IEEE Internet Things J.*, vol. 3, no. 3, pp. 428–438, Jun. 2016.

[8] Z. Zhou, J. Gong, Y. He, and Y. Zhang, "Software defined machine-to-machine communication for smart energy management," *IEEE Commun. Mag.*, vol. 55, no. 10, pp. 52–60, Oct. 2017.

[9] Z. Zhou, Y. Guo, Y. He, X. Zhao, and W. M. Bazzi, "Access control and resource allocation for M2M communications in industrial automation," *IEEE Trans. Ind. Informat.*, vol. 15, no. 5, pp. 3093–3103, May 2019.

[10] M. Liu, J. Yang, T. Song, J. Hu, and G. Gui, "Deep learning-inspired message passing algorithm for efficient resource allocation in cognitive radio networks," *IEEE Trans. Veh. Technol.*, vol. 68, no. 1, pp. 641–653, Jan. 2018.

[11] J. Wu, M. Dong, K. Ota, J. Li, and Z. Guan, "FCSS: Fog computing based content-aware filtering for security services in information centric social networks," *IEEE Trans. Emerg. Topics Comput.*, to be published. doi: 10.1109/TETC.2017.2747158.

[12] N. Zhang, P. Yang, S. Zhang, D. Chen, W. Zhuang, B. Liang, and X. S. Shen, "Software defined networking enabled wireless network virtualization: Challenges and solutions," *IEEE Netw.*, vol. 31, no. 5, pp. 42–49, May 2017.

[13] F. Tang, Z. Md Fadlullah, N. Kato, F. Ono, and R. Miura, "AC-POCA: Anti-coordination game based partially overlapping channels assignment in combined UAV and D2D based networks," *IEEE Trans Veh. Technol.*, vol. 67, no. 2, pp. 1672–1683, Feb. 2018.

[14] Y. Qiao, Y. Cheng, J. Yang, J. Liu, and N. Kato, "A mobility analytical framework for big mobile data in densely populated area," *IEEE Trans. Veh. Technol.*, vol. 66, no. 2, pp. 1443–1455, Feb. 2017.

[15] X. Wang, M. Jia, I. W.-H. Ho, Q. Guo, and F. C. M. Lau, "Exploiting full-duplex two-way relay cooperative non-orthogonal multiple access," *IEEE Trans. Commun.*, vol. 67, no. 4, pp. 2716–2729, Apr. 2019.

[16] M. Jia, X. Wang, Q. Guo, I. W.-H. Ho, X. Gu, and F. Lau, "Performance analysis of cooperative non-orthogonal multiple access based on spectrum sensing," *IEEE Trans. Veh. Technol.*, vol. 68, no. 7, pp. 6855–6866, Jul. 2019.

[17] M. Jia, L. Wang, Q. Guo, X. Gu, and W. Xiang, "A low complexity detection algorithm for fixed up-link SCMA system in mission critical scenario," *IEEE Internet Things J.*, vol. 5, no. 5, pp. 3289–3297, Oct. 2018.

[18] M. Jia, Z. Yin, Q. Guo, G. Liu, and X. Gu, "Downlink design for spectrum efficient IoT network," *IEEE Internet Things J.*, vol. 5, no. 5, pp. 3397–3404, Oct. 2018.

[19] S. Cicalo, B. Sayadi, F. Faucheux, V. Tralli, S. Kerboeuf, and N. Changuel, "Improving QoE and fairness in HTTP adaptive streaming over LTE network," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 26, no. 12, pp. 2284–2298, Dec. 2015.

[20] I. V. S. Brito and G. B. Figueiredo, "Improving QoS and QoE through seamless handoff in software-defined IEEE 802.11 mesh networks," *IEEE Commun. Lett.*, vol. 21, no. 11, pp. 2484–2487, Nov. 2017.

[21] N. Kato, Z. M. Fadlullah, B. Mao, F. Tang, O. Akashi, T. Inoue, and K. Mizutani, "The deep learning vision for heterogeneous network traffic control: Proposal, challenges, and future perspective," *IEEE Wireless Commun.*, vol. 24, no. 3, pp. 146–153, Jun. 2017.

[22] N. Kato, "Challenges of content-centric mobile networks," *IEEE Netw.*, vol. 31, no. 1, p. 2, Jan./Feb. 2017.

[23] S. Tan and M. L. Mayrovouniotis, "Reducing data dimensionality through optimizing neural network inputs," *AIChE J.*, vol. 41, no. 6, pp. 1471–1480, Jun. 1995.

[24] M. I. Abdulhussain and J. Q. Gan, "An experimental investigation on PCA based on cosine similarity and correlation for text feature dimensionality reduction," in *Proc. 7th Comput. Sci. Electron. Eng. Conf. (CEEC)*, Colchester, U.K., Sep. 2015, pp. 1–4.

[25] W. Sun and Q. Du, "Graph-regularized fast and robust principal component analysis for hyperspectral band selection," *IEEE Trans. Geosci. Remote Sens.*, vol. 56, no. 6, pp. 3185–3195, Jun. 2018.

[26] S. S. Shylaja, K. N. B. Murthy, and S. Natarajan, "Face recognition uiing trichotomic combination Of SVD, DF-LDA and LPP," in *Proc. 2nd Int. Conf. Comput. Automat. Eng. (ICCAE)*, vol. 1, Feb. 2010, pp. 246–250.

[27] X. Li, "Joint multilabel classification with community-aware label graph learning," *IEEE Trans. Image Process.*, vol. 25, no. 1, pp. 484–493, Jan. 2016.

[28] T. Zhou, S. Yang, L. Wang, J. Yao, and G. Gui, "Improved cross-label suppression dictionary learning for face recognition," *IEEE Access*, vol. 6, pp. 48716–48725, 2018.

[29] L. Shao, M. Li, L. Yuan, and G. Gui, "InMAS: Deep learning for designing intelligent making system," *IEEE Access*, vol. 7, pp. 51104–51111, 2019.

[30] J. Pan, Y. Yin, J. Xiong, W. Luo, G. Gui, and H. Sari, "Deep learning-based unmanned surveillance systems for observing water levels," *IEEE Access*, vol. 6, pp. 73561–73571, 2018.

[31] Y. Zhao, Q. Chen, W. Cao, J. Yang, J. Xiong, and G. Gui, "Deep learning for risk detection and trajectory tracking at construction sites," *IEEE Access*, vol. 7, pp. 30905–30912, 2019.

[32] J. Sun, W. Shi, Z. Han, J. Yang, and G. Gui, "Behavioral modeling and linearization of wideband RF power amplifiers using BiLSTM networks for 5G wireless systems," *IEEE Trans. Veh. Technol.*, to be published. doi: 10.1109/TVT.2019.2925562.

[33] R. Kajale, S. Das, and P. Medhekar, "Supervised machine learning in intelligent character recognition of handwritten and printed nameplate," in *Proc. Int. Conf. Adv. Comput., Commun. Control (ICAC3)*, Dec. 2017, pp. 1–5.

[34] Z. M. Fadlullah, F. Tang, B. Mao, N. Kato, O. Akashi, T. Inoue, and K. Mizutani, "State-of-the-art deep learning: Evolving machine intelligence toward tomorrow's intelligent network traffic control systems," *IEEE Commun. Surveys Tuts.*, vol. 19, no. 4, pp. 2432–2455, Apr. 2017.

[35] Z. M. Fadlullah, F. Tang, B. Mao, J. Liu, and N. Kato, "On intelligent traffic control for large-scale heterogeneous networks: A value matrix-based deep learning approach," *IEEE Commun. Lett.*, vol. 22, no. 12, pp. 2479–2482, Dec. 2018.

[36] F. Tang, Z. Md Fadlullah, B. Mao, and N. Kato, "An intelligent traffic load prediction-based adaptive channel assignment algorithm in SDN-IoT: A deep learning approach," *IEEE Internet Things J.*, vol. 5, no. 6, pp. 5141–5154, Dec. 2018.

[37] Z. M. Fadlullah, B. Mao, F. Tang, and N. Kato, "Value iteration architecture based deep learning for intelligent routing exploiting heterogeneous computing platforms," *IEEE Trans. Comput.*, vol. 68, no. 6, pp. 939–950, Jun. 2019.

[38] H. Huang, G. Gui, H. Sari, and F. Adachi, "Deep learning for optical character recognition and its application to VAT invoice recognition," in *Proc. Int. Conf. Commun., Signal Process., Syst. (CSPS)*, Dalian, China, Jul. 2018, pp. 1–10.

[39] H. Huang, G. Gui, H. Sari, and F. Adachi, "Deep learning for super-resolution DOA estimation in massive MIMO systems," in *Proc. IEEE 88th Veh. Technol. Conf. (VTC-Fall)*, Chicago, IL, USA, Aug. 2018, pp. 1–5.

[40] X. Gao, S. Jin, C.-K. Wen, and G. Y. Li, "ComNet: Combination of deep learning and expert knowledge in OFDM receivers," *IEEE Commun. Lett.*, vol. 22, no. 12, pp. 2627–2630, Dec. 2018.

[41] Y. Tu and Y. Lin, "Deep neural network compression technique towards efficient digital signal modulation recognition in edge device," *IEEE Access*, vol. 7, no. 1, pp. 58113–58119, 2019.

[42] G. Gui, H. Huang, Y. Song, and H. Sari, "Deep learning for an effective nonorthogonal multiple access scheme," *IEEE Trans. Veh. Technol.*, vol. 67, no. 9, pp. 8440–8450, Sep. 2018.

[43] J. Wang, Y. Ding, S. Bian, Y. Peng, M. Liu, and G. Gui, "UL-CSI data driven deep learning for predicting DL-CSI in cellular FDD systems," *IEEE Access*, vol. 7, pp. 96105–96112, 2019.

[44] H. Huang, "Deep learning for physical-layer 5G wireless techniques: Opportunities, challenges and solutions," *IEEE Wireless Commun.*, to be published. doi: 10.1109/MWC.2019.1900027.

[45] H. Huang, W. Xia, J. Xiong, J. Yang, G. Zheng, and X. Zhu, "Unsupervised learning based fast beamforming design for downlink MIMO," *IEEE Access*, vol. 7, pp. 7599–7605, 2018.

[46] Y. Wang, M. Liu, J. Yang, and G. Gui, "Data-driven deep learning for automatic modulation recognition in cognitive radios," *IEEE Trans. Veh. Technol.*, vol. 68, no. 4, pp. 4074–4077, Apr. 2019.

[47] Z. Chen, C. K. Yeo, B. S. Lee, and C. T. Lau, "Autoencoder-based network anomaly detection," in *Proc. Wireless Telecommun. Symp. (WTS)*, Phoenix, AZ, USA, Apr. 2018, pp. 1–5.

[48] D. Lam, M. Wei, and D. Wunsch, "Clustering data of mixed categorical and numerical type with unsupervised feature learning," *IEEE Access*, vol. 3, pp. 1605–1613, 2015.

[49] X.-W. Li and Y.-F. Qi, "A data preprocessing algorithm for classification model based on rough sets," *Phys. Procedia*, vol. 25, pp. 2025–2029, Jan. 2012.

[50] Y. Liu, S. Liu, Y. Wang, F. Lombardi, and J. Han, "A stochastic computational multi-layer perceptron with backward propagation," *IEEE Trans. Comput.*, vol. 67, no. 9, pp. 1273–1286, Sep. 2018.

[51] F. Yang, L. Yang, D. Wang, P. Qi, and H. Wang, "Method of modulation recognition based on combination algorithm of K-means clustering and grading training SVM," *China Commun.*, vol. 15, no. 12, pp. 55–63, Dec. 2018.

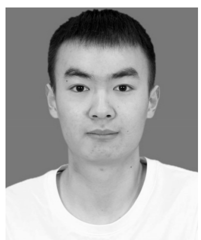
[52] I. Dokmanic, R. Parhizkar, J. Ranieri, and M. Vetterli, "Euclidean distance matrices: Essential theory, algorithms, and applications," *IEEE Signal Process. Mag.*, vol. 32, no. 6, pp. 12–30, Nov. 2015.

[53] S. Agarwal, P. Ranjan, and A. Ujlayan, "Comparative analysis of dimensionality reduction algorithms, case study: PCA," in *Proc. 11th Int. Conf. Intell. Syst. Control (ISCO)*, Coimbatore, India, Jan. 2017, pp. 255–259.

[54] L. Gong and A. K. Nandi, "Clustering by non-negative matrix factorization with independent principal component initialization," in *Proc. 21st Eur. Signal Process. Conf. (EUSIPCO)*, Marrakech, Morocco, Sep. 2013, pp. 1–5.

KAIXUAN ZHANG (S'18) is currently pursuing the master's degree in communication and information engineering with the Nanjing University of Posts and Telecommunications, Nanjing, China. His research interest includes machine learning for wireless communications.

WENJUAN SHI (M'19) received the M.S. degree in mechatronics from Soochow University, Suzhou, China, in 2006, and the Dr. Eng. degree in information and control engineering from the China University of Mining and Technology, in 2018. Since 2017, she has been an Associate Professor with Yancheng Teachers University and a Visiting Scholar with the Nanjing University of Posts and Telecommunications. Her current research interests include deep learning, video quality assessment, and image processing.



JUN ZENG (S'18) is currently pursuing the master's degree in communication and information engineering with the Nanjing University of Posts and Telecommunications, Nanjing, China. His research interest includes machine learning for wireless communications.

GUANGHUI FAN (S'18) is currently pursuing the master's degree in communication and information engineering with the Nanjing University of Posts and Telecommunications, Nanjing, China. His research interest includes machine learning for wireless communications.

YU WANG (S'18) received the B.S. degree in communication engineering from the Nanjing University of Posts and Telecommunications (NUPT), Nanjing, China, in 2018, where he is currently pursuing the Ph.D. degree. He has published eight international peer-reviewed journal/conference papers. His research interests include deep learning, optimization, and its application in wireless communications. He received four Best Paper Awards, such as ICEICT 2019, CSPS 2019, and CSPS 2018.

GUAN GUI (M'11–SM'17) received the Dr. Eng degree in information and communication engineering from the University of Electronic Science and Technology of China (UESTC), Chengdu, China, in 2012.

From October 2009 to March 2012, with the financial support from the China Scholarship Council (CSC) and the Global Center of Education (ECOE) of Tohoku University, he joined the Wireless Signal Processing and Network Laboratory, Department of Communications Engineering, Graduate School of Engineering, Tohoku University, as a Research Assistant and a Postdoctoral Research Fellow. From September 2012 to March 2014, he was supported by the Japan Society for the Promotion of Science (JSPS) Fellowship as a Postdoctoral Research Fellow with the Wireless Signal Processing and Network Laboratory. From April 2014 to October 2015, he was an Assistant Professor with the Department of Electronics and Information System, Akita Prefectural University. Since November 2015, he has been a Professor with the Nanjing University of Posts and Telecommunications (NJUPT), Nanjing, China. He is currently involved in research on deep learning, compressive sensing, and intelligent wireless techniques. He has published more than 200 international peer-reviewed journal/conference papers. He received the Member and Global Activities Contributions Award of the IEEE ComSoc and eight best paper awards, ICEICT 2019, CSPS 2019, ADHIP 2018, CSPS 2018, ICNC 2018, ICC 2017, ICC 2014, and VTC 2014-Spring. He was also selected as a Jiangsu Specially Appointed Professor, in 2016 and for the Jiangsu High-level Innovation and Entrepreneurial Talent, in 2016, the Jiangsu Six Top Talent, in 2018, and the Nanjing Youth Award, in 2018. He was an Editor of *Security and Communication Networks*, from 2012 to 2016. He has been an Editor of the IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY, since 2017, IEEE ACCESS, since 2018, *Physical Communication* journal, since 2019, *KSII Transactions on Internet and Information Systems*, since 2017, and the Journal of Communications, since 2019, and the Editor-in-Chief of *EAI Transactions on Artificial Intelligence*, since 2018.