Deep Learning Network Based Spectrum Sensing Methods for OFDM Systems

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Abstract—Spectrum sensing plays a critical role in dynamic spectrum access, a promising technology to address the radio spectrum shortage. In particular, sensing of orthogonal frequency division multiplexing (OFDM) signals, a widely accepted multi-carrier transmission paradigm, has received paramount interest. Despite various efforts, most conventional OFDM sensing methods suffer from noise uncertainty, timing delay and carrier frequency offset (CFO) that significantly degrade the sensing accuracy. To address these challenges, this work develops two novel OFDM sensing frameworks drawing support from deep learning networks. Specifically, we first propose a stacked autoencoder based spectrum sensing method (SAE-SS), in which a stacked autoencoder network is designed to extract the hidden features of OFDM signals. Using these features to classify the OFDM user’s activities, SAE-SS is much more robust to noise uncertainty, timing delay, and CFO than the conventional OFDM sensing methods. Moreover, SAE-SS doesn’t require any prior information of signals (e.g., signal structure, pilot tones, cyclic prefix) which are essential for the conventional feature-based OFDM sensing methods. To further improve the sensing accuracy of SAE-SS, especially under low SNR conditions, we propose a stacked autoencoder based spectrum sensing method using time-frequency domain signals (SAE-TF). SAE-TF achieves higher sensing accuracy than SAE-SS at the cost of higher computational complexity. Extensive simulation results show that both SAE-SS and SAE-TF can achieve significantly higher sensing accuracy, compared with state of the art approaches that suffer from noise uncertainty, timing delay and CFO.

Index Terms—Spectrum sensing, OFDM, deep learning, SAE.

I. INTRODUCTION

DYNAMIC spectrum access (DSA) or spectrum sharing has been widely considered as a promising solution to the spectrum shortage problem. Standard bodies like the Federal Communications Commission (FCC) and the European Telecommunications Standardization Institute (ETSI) have been proposing spectrum management frameworks (e.g., Spectrum Access Systems by FCC and Licensed Shared Access by ETSI) that adopt spectrum sharing as a core feature. Under DSA, licensed but underutilized spectrum bands of primary/incumbent users (IUs) are open for secondary users (SUs) with different access priority levels. To avoid harmful interference to IUs as well as to comply with the granted priority right, SUs are required to detect the activity states of IUs (e.g., absence or presence). Reliable spectrum sensing allows SUs to occupy or evacuate the spectrum bands, depending on the activity of IUs and other prioritized users. As a widely accepted multi-carrier transmission paradigm, sensing of orthogonal frequency division multiplexing (OFDM) signals has received paramount interest.

The existing signal sensing methods in the literature can be categorized into: non-cooperative and cooperative sensing. For the former, the sensing decision (on IU activity) is made solely by a single SU. For the latter, each SU makes a local decision and all those decisions are reported to a fusion center to achieve a final decision based on some fusion rules. In this work, we focus on the non-cooperative OFDM sensing methods.

The energy detection (ED) is one of the simplest and most popular sensing methods, which assesses IU’s activity states based on the energy of the received signals. This approach is particularly vulnerable to noise uncertainty that would significantly degrade the sensing accuracy. In comparison to ED, the matched filtering (MF) based sensing method, which detects the presence of IU’s signals by correlating a known waveform with the input signals, is more robust to noise uncertainty. However, MF is sensitive to the timing delay.

To leverage the special features of OFDM signals, e.g., pilot tones (PT), cyclic prefix (CP), and covariance matrix (CM) features, one can use the feature-based detection approach. For instance, authors of and propose methods to detect the activity states of IUs by utilizing features of PT, e.g., the cross-correlation of the time-domain symbols and the statistical difference between the pilot and payload subcarriers, respectively. Although these PT-based methods can reliably detect IU’s signals, they have high computational complexities and are vulnerable to the carrier frequency offset (CFO). and and present methods to detect the IU’s signals by exploiting the characteristics of CP, i.e., autocorrelation and cyclostationarity properties, respectively. In, authors propose a CM-based method to determine the IU’s activity states by leveraging the features of the covariance matrix of the discrete Fourier transform of the received signals. However, the sensing accuracies of these CP-based and CM-based methods are heavily dependent on the synchronization errors/timing delay. It is worth noting that all feature-based methods require full or partial prior knowledge of IU’s signals (e.g., IU’s transmitting power, the CP or PT structure of IU signals) and/or noise power that are

1Without loss of generality, in this work, we refer to all higher prioritized users (including IUs) as IUs and to lower prioritized users as SUs.
unavailable in some practical applications (e.g., when IUs are military applications) \[18\]. Instead of requiring features as a priori knowledge, in this work, we employ the latest advances in machine learning (ML) \[19\], \[20\] to learn them. More importantly, our methods can also learn/reveal the unknown hidden features (but having some special structures) of OFDM signals to improve the sensing accuracy.

ML has recently found its applications in various areas such as object detection \[21\], \[22\], speech recognition \[23\], \[24\], channel estimation \[25\], and pattern recognition \[26\], \[27\], \[28\]. We observe that spectrum/signal sensing resembles a pattern recognition problem, as illustrated in Fig. 1. Specifically, pattern recognition involves the steps of the feature extraction and the classification \[29\]. Analogously, typical OFDM sensing methods consist of two steps: first, calculate the test statistic of the received signals; second, compare the test statistic with the corresponding thresholds to detect IU’s activity. We then can map these first and second stages in OFDM sensing to the feature extraction and the classification in pattern recognition, respectively. For example, the authors in \[30\] present an artificial neural network based sensing algorithm, which uses the energy feature as the input feature. In \[31\] and \[32\], authors apply both the energy and cyclostationary features as the input feature and propose spectrum sensing methods based on artificial neural networks, respectively. Although these ML-based sensing methods can improve the sensing accuracy, they learned specific/known features from the original received signals can only obtain partial information. That process inevitably loses information, i.e., unknown but helpful features.

We leverage deep learning networks to overcome all the limitations as mentioned above. Deep learning (DL) \[33\], \[34\] relies on a deep architecture with multiple layers of nonlinear processing units to extract and transform the hidden features of the input signals. In this work, we present two sensing methods drawing support from the stacked autoencoder (SAE) \[35\] to detect IU’s activity states. Our major contributions are summarized as follows.

- We propose the stacked autoencoder based spectrum sensing method (SAE-SS) to extract hidden features of the original received signals and detect the IU’s activities based on the extracted features.
- Compared with traditional OFDM sensing methods, the proposed SAE-SS is more robust to timing delay, noise uncertainty and CFO. More importantly, SAE-SS can sense the IUs activity states using only the original received signals (i.e., without requiring any prior knowledge of the IUs signal structure).
- Unlike the existing ML-based OFDM sensing methods that require external algorithms to extract some specific features from the original received signals for sensing purpose, SAE-SS automatically extracts all hidden features from the original received signals (i.e., without any additional feature extraction algorithms).
- To further improve the sensing accuracy of SAE-SS, especially under low SNR conditions, we propose a stacked autoencoder based spectrum sensing method using time-frequency domain signals (SAE-TF). SAE-TF achieves higher sensing accuracy by the cost of higher computational complexity.

We carry out extensive simulations to evaluate the performance of SAE-SS and SAE-TF, respectively. Experimental results are shown in Section \[\*\] followed by conclusions in Section \[\*\].
$h_i$ are assumed to be mutually independent. According to the central limit theorem, when the length of the received signals is sufficiently large, $s_m(n)$ approximately obeys the complex Gaussian distribution, and its mean and variance are zero and $\sigma_w^2$, respectively. In that case, SNR of $y_m(n)$ under $H_1$ can be represented as $\text{SNR} = \frac{\sigma_s^2}{\sigma_w^2} \sum_{l=0}^{L-1} |h_l|^2 / \sigma_w^2$.

### B. Problem Formulation

For typical OFDM sensing methods, e.g., the basic ED, its test statistic $T_{ED}$ is:

$$T_{ED} = \frac{1}{M(N_c + N_d)} \sum_{m=0}^{M-1} \sum_{n=0}^{N_c+N_d-1} |y_m(n)|^2.$$  \hspace{1cm} (2)

The probability of false alarm (PFA) and probability of miss detection (PM) for energy detection are

$$\text{PFA}_{ED} = \text{Pr}(T_{ED} > \lambda | H_0),$$

$$\text{PM}_{ED} = 1 - \text{Pr}(T_{ED} > \lambda | H_1),$$ \hspace{1cm} (3)

where $\text{Pr}(\cdot)$ denotes the probability distribution function. $\lambda$ is the sensing threshold based on the estimated noise variance ($\hat{\sigma}_w^2$). According to equations (2) and (3), ED only utilizes the received signals to detect the presence of IU without requiring any prior knowledge of IU signals. However, it is vulnerable to noise uncertainty. Moreover, even a small estimated error in the noise power would significantly deteriorate its sensing accuracy, especially in the low SNR regime [9].

For feature-based detections, such as CP-based [13] and CM-based sensing methods [16], their test statistics are

$$T_{CP} = \log \left( \frac{\max_{\sigma_s^2, \sigma_w} \text{Pr}(\mathbf{R} | H_1, \sigma_s^2, \sigma_w^2)}{\max_{\sigma_s^2, \sigma_w} \text{Pr}(\mathbf{R} | H_0, \sigma_s^2, \sigma_w^2)} \right),$$ \hspace{1cm} (4)

$$T_{CM} = \frac{\| \mathbf{R} \odot (\mathbf{I}_{N_d} - \mathbf{I}_{N_s}) \|_{L_1}}{\sqrt{N_x^2 - N_d}},$$ \hspace{1cm} (5)

where $\mathbf{R}$ is the correlation vector of the received signals. $\hat{\mathbf{R}}$ is the covariance matrix of received signals after discarding the CP in frequency domain.

### III. STACKED AUTOENCODER BASED SPECTRUM SENSING

In this section, we propose SAE-SS that is robust to timing delay, noise uncertainty and CFO. The architecture of the OFDM system with SAE-SS is shown in Fig. 3. The hidden features of received OFDM signals are extracted from the SAE network during the offline training stage. Those extracted features are then used to sense IU’s activity during the online sensing stage. The key steps of SAE-SS can be summarized as: pretraining, fine-tuning of SAE, and classification (e.g., online spectrum sensing stage).

#### A. Pretraining of Stacked Autoencoder

The pretraining SAE aims to learn the hidden features of received signals through two stages. In the first stage, the SAE network is divided into independent Autoencoders (AEs) and these AEs are individually trained, one by one. Note that each AE is a three-layer network that includes input layer, hidden layer and reconstruction layer, which is illustrated in Fig. 4(a). In the second stage, the input and hidden layers of all the trained AEs are stacked together, layer by layer, as shown in Fig. 4(b).

In this work, the number of input units for the first AE is only suitable for the non-complex numbers, we partition the
input signals into the real and imaginary parts, respectively. The received signal in equation (1) is rewritten as:

\[ y_1 := \{ \Re(y_1(0)), \Im(y_1(0)), \Re(y_1(1)), \Im(y_1(1)), \ldots, \Re(y_1(N_c + N_d - 1)), \Im(y_1(N_c + N_d - 1)) \}, \] (6)

where \( \Re(.) \) and \( \Im(.) \) mean the real part and the imaginary part, respectively. Thus the input vector of SAE-SS network \( x \) can be expressed as

\[ x := \{ y_0, y_1, \ldots, y_{M-1} \}^T, \] (7)

where the length of \( x \) is equal to \( N_{\text{input}} = 2M(N_c + N_d) \). Then the input signals \( x \) are used to train AEs. Take the \( l \)th AE as an example, let \( H_{l,p}^{in}, H_{l,k} \) and \( H_{l,q}^{out} \) denote the \( p \)th input unit, the \( k \)th hidden unit and the \( q \)th output unit, respectively. Then \( H_{l,k} \) can be obtained with \( H_{l,p}^{in} \), as shown below:

\[ H_{l,k} = f \left( \sum_{p=1}^{P_l} W_{l,p,k} H_{l,p}^{in} + b_{l,k} \right), \] (8)

where \( P_l \) is the number of input units in the \( l \)th AE. \( f(.) \) is activation function. \( W_{l,p,k} \) denotes the weight between the \( p \)th input unit and the \( k \)th hidden unit of the \( l \)th AE. \( b_{l,k} \) is the bias of the \( k \)th hidden unit of the \( l \)th AE. Then \( H_{l,q}^{out} \) can be achieved with \( H_{l,p}^{in} \) and \( H_{l,k} \), by

\[ H_{l,q}^{out} = f \left( \sum_{k=1}^{K_l} W_{l,k,q} H_{l,k} + b_{l,q} \right) \]

\[ = f \left( \sum_{k=1}^{K_l} W_{l,k,q} f \left( \sum_{p=1}^{P_l} W_{l,p,k} H_{l,p}^{in} + b_{l,k} \right) + b_{l,q} \right), \] (9)

where \( K_l \) is the number of units in the hidden layer of the \( l \)th AE. \( W_{l,k,q} \) denotes the weight between the \( k \)th hidden unit and the \( q \)th output unit of the \( l \)th AE. \( W_{l,k,q} = W_{l,k,q}^\prime + b_{l,q}^\prime \) is the bias of the \( q \)th output unit of the \( l \)th AE.

When \( l = 1 \), then the input vector \( H_{1}^{in} \) is same as \( x \), which is

\[ H_{1}^{in} := \{ H_{11}^{in}, H_{12}^{in}, \ldots, H_{1P_1}^{in} \}^T, \] (10)

where \( P_1 \) is the number of input units in the first AE, \( P_1 = N_{\text{input}} = 2M(N_c + N_d) \).

In this paper, the sigmoid function \([36]\) is adopted as the activation function, which is expressed as:

\[ f(H_{l,p}^{in}) = \frac{1}{1 + e^{-H_{l,p}^{in}}}. \] (11)

The aim of training the \( l \)th AE is to minimize the error between \( H_{l,p}^{in} \) and \( H_{l,p}^{out} \) by continuously updating the values of \( W_{l,p,k}, b_{l,k} \) and \( b_{l,q} \). The most typical error function to measure the difference between \( H_{l,p}^{in} \) and \( H_{l,p}^{out} \) is the mean square error:

\[ \chi = \frac{1}{P_l} \sum_{p=1}^{P_l} \left| H_{l,p}^{in} - H_{l,p}^{out} \right|^2. \] (12)

However, this method is time-consuming for training, thus we select the cross-entropy method \([37]\) to speed up the training process, which is

\[ \chi = \sum_{p=1}^{P_l} [H_{l,p}^{in} \log(H_{l,p}^{out}) + (1 - H_{l,p}^{in}) \log(1 - H_{l,p}^{out})]. \] (13)

Let \( \Omega = \{ W_{l,p,k}, b_{l,k}, b_{l,q} \} \), then the objective function is

\[ \Omega = \arg \min \chi. \] (14)

Moreover, we adopt the gradient descent method \([38]\) to achieve the optimal \( \Omega \), and the rules of updating \( \Omega \) are

\[ W_{l,p,k}(n+1) \leftarrow W_{l,p,k}(n) - \kappa \frac{\partial \chi(H_{l,p}^{in}, H_{l,p}^{out})}{\partial W_{l,p,k}}, \] (15)

\[ b_{l,k}(n+1) \leftarrow b_{l,k}(n) - \kappa \frac{\partial \chi(H_{l,p}^{in}, H_{l,p}^{out})}{\partial b_{l,k}}, \] (16)

\[ b_{l,q}(n+1) \leftarrow b_{l,q}(n) - \kappa \frac{\partial \chi(H_{l,p}^{in}, H_{l,p}^{out})}{\partial b_{l,q}}, \] (17)

where \( W_{l,p,k}(n), b_{l,k}(n) \) and \( b_{l,q}(n) \) denote the weight and bias of \( l \)th training. \( \kappa \) is the learning rate.

Upon training all the AEs based on the above rules, the trained SAE is created by stacking the input and hidden layers of trained AEs together, layer by layer. The output of SAE’s
pre-training, which is also the hidden units of Lth AE, can be written as
\[ H_L := \{H_{L,1}, H_{L,2}, \ldots, H_{L,K_L}\}^T, \quad (18) \]
where \( K_L \) is the number of units in the hidden layer of the Lth AE. \( H_L \) in equation (13) contains the hidden features of the received signals and will be used to sense the IU’s activity states.

**B. Fine-Tuning and Classification**

The pretraining process of SAE can be interpreted as extracting the IU’s unsupervised features. Thus, the trained SAE needs to be fine-tuned to leverage the SAE’s property for the spectrum sensing. In this paper, we select the logistic regression classifier [39] to fine-tune the SAE network, as shown in Fig. 4(b).

The logistic regression classifier can be regarded as a neural network with a single layer, and the activation of output layer is the softmax function. The input of the logistic regression classifier is \( H_L \), which is the output of the pretraining SAE. \( U \), the output of logistic regression classifier, can be seen as a set of conditional probabilities of \( H_L, W_R \) and \( b_R, W_R \) and \( b_R \) are weights and biases of the logistic regression layer.

Let \( \tau = 1 \) and \( \tau = 0 \) denote the presence and the absence of IU activity states, respectively. According to the logistic regression classifier [39], the conditional probability of \( U \) is:
\[ \Pr(U = \tau | H_L, W_R, b_R) = \frac{e^{W_{R,\tau} H_L + b_{R,\tau}}}{\sum_{i=0} e^{W_{R,i} H_L + b_{R,i}}}, \quad (19) \]

We apply the back-propagation method [40] to train the logistic regression classifiers. The whole SAE network is also fine-tuned at the same time. Upon pretraining and fine-tuning the SAE network in the offline phase, SAE-SS can detect the IU’s activity states using only the received signals. In comparison with the feature-based OFDM spectrum sensing methods (e.g., CP-based [13], CM-based [16] and ANN-based [30]), the inputs of SAE-SS are the originally received signals. SAE-SS does not require any arithmetical operations such as calculating the energy or the correlation values. Consequently, the overhead of SAE-SS during the online sensing stage is reduced significantly. Moreover, the proposed SAE-SS can complete the sensing task without any prior knowledge of the IU’s information, which is more suitable for the practical environment. That is particularly relevant to military applications, opening up the military radar bands for secondary use. The procedure of SAE-SS is summarized in the pseudo-code in Algorithm 1.

**Algorithm 1: Stacked Autoencoder Based Spectrum Sensing Method (SAE-SS)**

1. **begin**
2. **Initialize**: the length of input \( N_{input} \), number of SAE layer \( L \), the number of hidden unit in \( l \)th layer \( K_l \), pretraining iterations \( N_{pr} \), pre-training learning rate \( \kappa_p \), fine-tuning iterations \( N_f \), fine-tuning rate \( \kappa_f \), number of classes \( C \);
3. **Achieve** \( \kappa \) based on \( y \);
4. For \( 1 \leq l \leq L \)
5. **Build** an AE with \( N_u \) units of input layer and \( N_h \) unit of hidden layer;
6. **If** \( l = 1 \)
7. \( N_u = N_{input} \);
8. \( N_h = K_1 \);
9. \( \kappa \) is set as the input of AE;
10. **else**
11. \( N_u = P_l \);
12. \( N_h = K_l \);
13. \( \kappa \) is the hidden units of previous layer \( H_{l-1} \) is set as the input of current layer \( H_l^\ast \);
14. **end**
15. Initialize AE, generate \( W_i, b_i = b_i' = 0 \)
16. For \( 1 \leq l \leq N_{pr} \)
17. Based on (9) calculate the output of reconstruction:
18. \[ H_{l}^{out} = f(\sum_{k=1}^{K_l} W_{l,k,q} H_{l,k} + b_{l,q}) \]
19. **Based on** (13) calculate the error:
20. \[ \chi = \sum_{p=1}^{P_l} [H_{l,p_q}(H_{l,p}^{out}) + (1 - H_{l,p_q}^{out}) \log(1 - H_{l,p}^{out})] \]
21. **Based on** (15)-(17) update \( W_i, b_i \) with \( \kappa_p \)
22. **end**
23. **Remove** the reconstruction layer of AE
24. **end**
25. **Initialize** logistic regression layer: \( K_L \) unit of input layer, \( C \) unit of output layer
26. For \( 1 \leq l \leq N_f \)
27. Based on (19) calculate probability of each class
28. **Based on** back propagation, update parameters of every layer with \( \kappa_f \)
29. **end**
30. **end**
31. **end**

IV. STACKED AUTOENCODER BASED SPECTRUM SENSING WITH TIME-FREQUENCY DOMAIN SIGNALS

As aforementioned, the proposed SAE-SS achieves high sensing accuracy by extracting all hidden (known and unknown) features of the received OFDM signals without requiring any external feature extraction algorithms. However, its sensing accuracy would degrade under low SNR conditions. To address that problem, we present a Stacked Autoencoder Based Spectrum Sensing Method with time-frequency domain signals (SAE-TF). The input data of SAE-TF involves both time domain and frequency domain signals, which are beneficial for SAE to extract more hidden features for the spectrum sensing purpose. The framework of SAE-TF is shown in Fig. 5.

The first step of SAE-TF is to transfer the original received signals from the time domain to the frequency domain by Fast Fourier transform (FFT):
\[ Y = \text{FFT}(y), \quad (20) \]
where \( \text{FFT}(\cdot) \) denotes the FFT operation. Then \( Y \) is divided into real and imaginary parts, respectively. Under this situation, the frequency domain signals are expressed as:
\[ \begin{align*}
Y_t := \{\Re(Y_t(0)), \Im(Y_t(0)), \ldots, \\
\Re(Y_t(N_c + N_d - 1)), \Im(Y_t(N_c + N_d - 1))\}. \quad (21)
\end{align*} \]

Thus the frequency domain input vector of SAE-SS network \( X \) can be expressed as:
\[ X := \{Y_0, Y_1, \ldots, Y_{M-1}\}^T, \quad (22) \]
Then we provide the performance analysis of SAE-SS and SAE-TF with different parameters. The propagation channel between IU transmitter and SU receiver is a frequency selective Rayleigh fading channel. The OFDM block size of the IU signals is set to $N_d = 64$ and CP length is $N_c = N_d/8$. We set the probability of false alarm $P_{FA} = 0.05$. The number of hidden layers for both SAE-SS and SAE-TF is $L = 2$. The first and the second hidden layer contain 100 and 50 units, respectively. The number of received OFDM blocks is $M = 2$. The number of input units for SAE-SS and SAE-TF are $2M(N_c + N_d)$ and $2 \times 2M(N_c + N_d)$, respectively. The training data set and the testing data set contain $2 \times 10^4$ samples, respectively. The number of iterations is 5000. In this work, we use TensorFlow 1.3 with python language to train the proposed SAE-SS and SAE-TF for spectrum sensing. The experiments are conducted on the 6-Core 3.6GHz PC with Nvidia P5000 graphic card (16GB memory).

Fig. 6 shows the performance of extracted hidden features for SAE-SS and SAE-TF under SNR $= -15$dB, compared with the input signals of the first layer. Specifically, the first $10^4$ samples denote “IU is absent” and the second $10^4$ samples mean “IU is present”. The numbers of input data of the first layer for SAE-SS and SAE-TF are 288 and 576, respectively. For each method, the number of output signals of the second hidden layer is 50. According to Fig. 6(a) and Fig. 6(c), it is very difficult to differentiate between the “IU is absent” and “IU is present” based on the input signals only. However, they can be readily separated by the output signals of the second hidden layer as (much more clearly) visibly observed in Fig. 6(b) and Fig. 6(d). That is because SAE-SS and SAE-TF extract more hidden features from the received signals.

**Algorithm 2: Proposed Stacked Autoencoder Based Spectrum Sensing Method with Time-Frequency Domain Signals (SAE-TF)**

\begin{verbatim}
Algorithm 2: Proposed Stacked Autoencoder Based Spectrum Sensing Method with Time-Frequency Domain Signals (SAE-TF)
1: begin
2: Transfer the received signals $y$ using FFT and obtain $Y$
3: Achieve $x$ and $X$ based on $y$ and $Y$
4: For $1 \leq l \leq L$
5: Build an AE with $N_x$ units of input layer and $N_h$ units of hidden layer;
6: If $l = 1$
7: $N_v = 2 \times N_{input}$;
8: $N_h = K_1$;
9: The input signals of the first AE are the linear arrangement of $x$ and $X$
10: else
11: $N_v = P_l$;
12: $N_h = K_l$;
13: the hidden units of previous layer $H_{l-1}$ is set as the input of current layer $H_l$;
14: end
15: Train SAE-TF with the input signals.
Training procedures are the same to Summary 1.
16: end
\end{verbatim}

where the length of $X$ is equal to $2M(N_c + N_d)$.

Then the input signals, which are the linear arrangement of $x$ and $X$, are fed into the SAE network for training, as shown in Fig. 5. After pre-training, fine-tuning of SAE, which are the same as in Section III, SAE-TF can better probe the activity states of the IU than SAE-SS based on the extracted hidden features. Notably, SAE-TF outperforms SAE-SS with the help of time domain and frequency domain features. However, the number of input units of SAE-TF doubles that of SAE-SS, so the training complexity is higher, which will be described in Section V. The procedure of SAE-SS is summarized in the pseudo-code in Algorithm 2.

**V. SIMULATION RESULTS**

In this section, we first conduct simulations to analyze the performance of the proposed two methods (e.g., SAE-SS and SAE-TF) and other four conventional OFDM sensing methods (e.g., basic ED method, CP-based sensing method [13], CM-based sensing method [16], and ANN-based sensing method [50]). Then we provide the performance analysis of SAE-SS and SAE-TF with different parameters. The propagation channel between IU transmitter and SU receiver is a frequency selective Rayleigh fading channel. The OFDM block size of the IU signals is set to $N_d = 64$ and CP length is $N_c = N_d/8$. We set the probability of false alarm $P_{FA} = 0.05$. The number of hidden layers for both SAE-SS and SAE-TF is $L = 2$. The first and the second hidden layer contain 100 and 50 units, respectively. The number of received OFDM blocks is $M = 2$. The number of input units for SAE-SS and SAE-TF are $2M(N_c + N_d)$ and $2 \times 2M(N_c + N_d)$, respectively. The training data set and the testing data set contain $2 \times 10^4$ samples, respectively. The number of iterations is 5000. In this work, we use TensorFlow 1.3 with python language to train the proposed SAE-SS and SAE-TF for spectrum sensing. The experiments are conducted on the 6-Core 3.6GHz PC with Nvidia P5000 graphic card (16GB memory).

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Training procedures are the same to Summary 1.
16: end
\end{verbatim}

A. Comparison between Proposed Methods and Existing OFDM Spectrum Sensing Methods

In this subsection, we compare the values of PM under different conditions for six sensing methods: the proposed two methods (e.g., SAE-SS and SAE-TF), basic ED, CP-based [13], CM-based [16], and ANN-based sensing methods [50].

Fig. 7 compares the values of PM of different sensing methods under the “perfect condition”. In the perfect condition, the SU has sufficient prior knowledge of IU signals. Additionally, there is no effects of noise uncertainty, timing delay or carrier frequency offset. As can be seen, the values of PM of SAE-SS and SAE-TF are much smaller than the other four sensing methods. For instance, when SNR $= -20$dB, the PM of SAE-SS and SAE-TF are only 0.5189 and 0.3298, respectively. By contrast, the figures for ED, CM-based, CP-based, and ANN-based sensing methods are 0.8279, 0.9192, 0.8145, and 0.7413, respectively. Moreover, with the increase of SNR, the PM of SAE-SS and SAE-TF reduce much faster than the other four sensing methods.

Fig. 8 shows the impact of noise uncertainty $\eta$ on six sensing methods. According to this figure, it is clear that the proposed SAE-SS and SAE-TF are much more robust to noise uncertainty than the other four sensing methods. For instance, when $\eta$ increases from 0.5dB to 1dB under SNR $= -10$dB, PM of SAE-SS and SAE-TF only increase from 0.0155 to 0.0190
Fig. 6. The performance of extracting hidden features for SAE-SS and SAE-TF under SNR=-15dB

Fig. 7. Probability of miss detection among different spectrum sensing methods under perfect conditions

and from 0.0098 to 0.0114, respectively. On the contrary, PM of ANN-based, CP-based, CM-based, and ED methods

increase from 0.0845 to 0.1045, from 0.2549 to 0.3415, from 0.4213 to 0.5142, and from 0.4522 to 0.6450, respectively.

Fig. 9 compares the effect of timing delay on sensing
performance among the different sensing methods. Since ED is not affected by timing delay, we only present the sensing performance of SAE-SS, SAE-TF, CM-based, CP-based, and ANN-based sensing methods. The timing delay, $\delta$, is selected as $1$-symbol and $5$-symbol, respectively. It can be seen that in comparison with CM-based, CP-based and ANN-based sensing methods, SAE-SS and SAE-TF are more robust to the timing delay. Moreover, the PM of SAE-TF is still the smallest of these five sensing methods. For instance, when $\delta = 5$ symbol and $\text{SNR} = -12$ dB, the PM of SAE-SS and SAE-TF are $0.0679$ and $0.0418$, respectively. However, the PM of ANN-based, CM-based and CP-based are $0.2927$, $0.7281$ and $0.8756$, respectively.

Fig. 10 shows the impact of CFO on the five different sensing methods. The normalized CFO in this figure is set to $0.5$ and $1$, respectively. The sensing results of ED are not presented in this figure, because they are not affected by CFO. It is obvious that the proposed SAE-SS and SAE-TF outperform the CP-based, CM-based and ANN-based sensing methods regarding the robustness to CFO. The proposed SAE-SS and SAE-TF are capable of achieving much smaller PM than the other three sensing methods. Moreover, the PM of SAE-SS and SAE-TF increase slightly when the normalized CFO grows from $0.5$ to $1$. However, PM of the ANN-based, CM-based and CP-based methods increase significantly. For example, when $f_q = 1$ and $\text{SNR} = -10$ dB, PM of SAE-SS and SAE-TF are $0.0195$ and $0.0130$, respectively. However, those of ANN-based, CM-based and CP-based methods are $0.1873$, $0.7092$ and $0.5729$, respectively.

**B. Sensing Performance Analysis of SAE-SS and SAE-TF under Different Conditions**

In this subsection, we further analyze the sensing performance of the proposed SAE-SS and SAE-TF under different conditions.

Fig. 11 shows the impact of the number of hidden layers on SAE-SS and SAE-TF. The number of hidden layers is selected as $L = 1, 2, 3$, and the corresponding number of units in hidden layers are $(100)$, $(100, 50)$ and $(100, 50, 20)$, respectively. The number of OFDM blocks is $M = 2$. According to this figure, the values of PM for these two sensing methods are getting better with the increase of $L$. For example, when $L$ increases from $1$ to $3$, PM of SAE-SS and SAE-TF decrease from $0.8756$ to $0.4371$ and from $0.3260$ to $0.2213$, respectively. However, the complexities of these two methods would also increase, thus specific $L$ should be selected based on different circumstances.

Fig. 12 compares the values of PM for SAE-SS and SAE-TF with different number of units in hidden layers with $\text{SNR} = -18$ dB, $M = 2$ and $L = 2$. Regarding this figure, both of these two methods can achieve smaller values of PM with the increase in the number of units in hidden layers. Moreover,
the PM for SAE-TF decreases faster than that of SAE-SS when increasing the number of units in hidden layers.

Fig. 13 shows the sensing performance of SAE-SS and SAE-TF with different numbers of the received OFDM blocks $M$. According to this figure, it is obvious that the sensing performance of these two sensing methods is affected by the factor $M$. When $M$ changes from 1 to 3, SNR = $-10$ dB, the PM of SAE-SS declines by 0.0402, and the PM of SAE-TF decreases by 0.0221. Notably, the complexity also increases with the growth of $M$, which is captured by the training time recorded in Table I.

Table I shows the offline training time of SAE-SS and SAE-TF with a different number of OFDM blocks $M$. The number of hidden layers is $L = 2$, and there are 100 and 50 units in the first and second hidden layer, respectively. The training data set contains $10^6$ samples. The number of iterations is 20000. Based on this table, the offline training time of SAE-SS is bigger than that of SAE-SS. Moreover, with the increase of $M$, the offline training time of SAE-TF is increasingly longer than SAE-SS. Since SAE-TF can achieve higher sensing performance than SAE-SS, it provides a better tradeoff between accuracy and complexity.

VI. CONCLUSION

In this paper, we proposed a Stacked Autoencoder Based Spectrum Sensing Method (SAE-SS) and a Stacked Autoencoder Based Spectrum Sensing Method with time-frequency domain signals (SAE-TF) to detect the activity states of IUs using OFDM signal. SAE-SS and SAE-TF are more robust to timing delay, CFO, and noise uncertainty, compared with the conventional OFDM sensing methods. Moreover, they are able to detect IU’s activities solely based on the received signals and without any requirement of prior knowledge of IU’s signals. SAE-SS and SAE-TF also do not require any external feature extraction algorithms. SAE-TF achieves a better sensing accuracy than SAE-SS, especially under low SNR conditions, while it has the higher complexity. Extensive simulation results demonstrate that SAE-SS and SAE-TF are capable of achieving much higher sensing performance than traditional OFDM sensing methods even under low SNR and severe timing delay, CFO, and noise uncertainty conditions. This is thanks to the capability of the underlying deep neural networks of SAE-SS and SAE-TF that extract both known and unknown hidden features of OFDM signals.

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