LSTM Autoencoder aided Estimation of Primary Activity Statistics under Imperfect Sensing

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***Abstract*—Primary activity statistics contribute (PAS) significantly in increasing the efficiency of the dynamic spectrum access/cognitive radio system. PAS can be estimated from the spectrum sensing observations. To achieve a precise estimation of PAS, accurate spectrum sensing is required. However, it is difficult to maintain perfect spectrum sensing in a realistic scenario because of various hardware and sensing errors (false alarms and miss detections). In this work, Long-Short Term Memory autoencoder based deep learning framework is proposed to detect the sensing errors in imperfect spectrum sensing scenarios. Moreover, to correct the sensing errors, we propose a simple single iteration reconstruction algorithm and further estimate the PAS. The error in the estimated PAS is quantified through the Kolmogorov Smirnov distance. Finding suggests that relative error of estimated mean decreases from 80% to 9%. The proposed framework doesn't require any prior knowledge of PU activity statistics to achieve this performance making it feasible in realistic scenarios.**

***Index Terms*—LSTM autoencoder, Primary activity statistics, Reconstruction algorithms, Dynamic spectrum access, Imperfect spectrum sensing.**

I. Introduction

With the tremendous growth in wireless technology, IoT devices, and the emergence of 5G communication, the scarcity of wireless spectrum has arisen [1]. As per the survey carried out in [2], the overall utilization of spectrum resources ranges from 7% to 34%, leaving 66% unused. Dynamic Spectrum Access (DSA) based on Cognitive Radio (CR) technology is a promising solution for spectrum scarcity. DSA/CR systems exploit idle periods (spectrum holes) of the primary channel and allocate it to the secondary (unlicensed) users (SUs) without any interference to the primary users (PUs) [3]. This sensing decisions can be used to estimate a broad range of statistical information which is very useful to enhance spectrum utilization. To estimate accurate statistics, perfect spectrum sensing (PSS) scenario is needed which assumes a sufficiently high signal to noise ratio (SNR) but in realistic condition imperfect spectrum sensing (ISS) take place. ISS leads to the inaccurate observation of idle/busy periods causing erroneous estimation of statistics. Several attempts have been made to reconstruct the estimated idle/busy periods from the observation duration under ISS.

A detailed simulation-based study of ISS, its effect on the estimation of Primary activity statistics (PAS), and various reconstruction algorithms (RAs) are provided in [4] which were improved in [5]. Following this work, [6] provides a set of closed-form expressions, and a set of novel estimators to accurately estimate the PAS. Above mentioned algorithms assume perfect knowledge of the minimum periods for which PU is active, which in the realistic scenarios may be unknown to the DSA/CR system. This issue is addressed in [7], in which RA depends on the mean of idle/busy periods which is calculated using the mean estimator proposed in [8].

To acquire accurate results of spectrum sensing at low SNR is a challenging task for conventional methods. The emergence of Deep Learning (DL) in recent years has impacted many areas in the industry as well as academia and has shown great improvement compared to conventional methods. In [9] and [10], artificial neural network-based hybrid spectrum sensing framework is proposed which outperforms the conventional method of spectrum sensing. Following this work, in [11] Long-Short Term Memory (LSTM) and in [12], LSTM along with PAS are considered for spectrum sensing. Authors of [13] and [14] proposed a convolutional neural network (CNN) based approch for spectrum sensing which outperform model-based algorithms. A more complex model, namely as CNN-LSTM architecture is consider in [15] and [16] for effective spectrum sensing. In [17], detailed work on the feasibility of using DL for pro-active spectrum prediction is investigated. LSTM models are very effective in modeling the sequential data and finding in [18] suggests that spectrum occupancy data is in a sequential format. In this context, we exploit the capability of LSTM network to model the sequential data with the generative capability of autoencoder and propose a novel Long-Short Term Memory Autoencoder (LSTM-AE) based framework to detect sensing errors in sequential data and a simple single iteration RA to reconstruct the idle/busy period observed under ISS and estimated the PAS from reconstructed data, which to the best of the author's knowledge is new in the existing literature. This approach doesn't require any prior knowledge of statistics making it practically feasible with significant improvement in the estimation of PAS. The major contributions of the paper can be summarised as:

- Firstly, to model the spectrum occupancy data and learn the representation of the input, a novel deep learning based LSTM-AE framework is proposed. Model learns the latent representation of the original data which contains the features such as trend and cyclicity of the input data and use the learned representation of true data to detect the sensing error in the data observed under ISS.
- Secondly, to make the proposed error detection model robust and unbiased towards different sensing time (T_s), training data is prepared to include data at various sensing periods. This ensure that the error detection does not

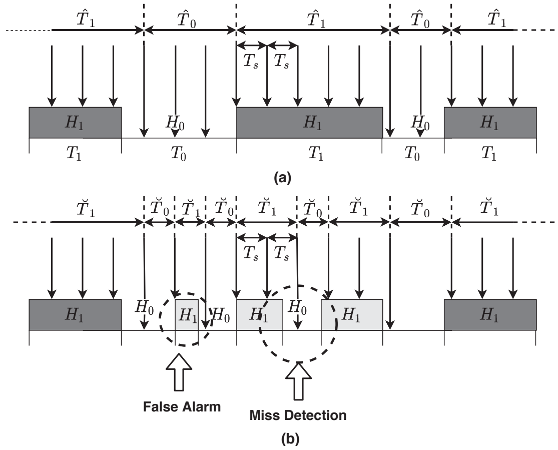

Fig. 1: Estimation of period duration from spectrum sensing decisions: (a) Perfect sensing, (b) Imperfect sensing.

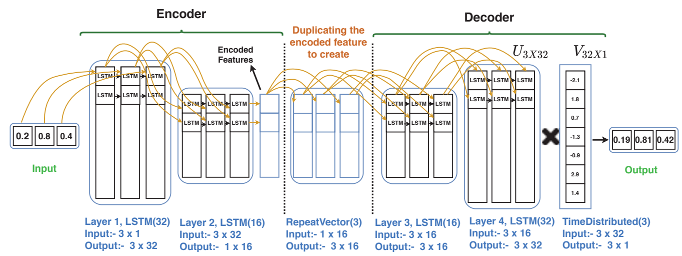

Fig. 2: LSTM autoencoder model architecture

deteriorate for different sensing time.

- Thirdly, a simple RA is proposed to correct the sensing errors detected by LSTM model in a single iteration.
- Morever, the proposed LSTM model and RA is validated on the prepared dataset with different duty cycle (Ψ), i.e., $\Psi = 0.5$ & $\Psi = 0.8$ and a comparison is provided to quantify the accuracy gain in calculation of PAS using the proposed method.

II. System Model

Fig. 1 describes the occupancy pattern of a single PU. It consists of idle/busy periods sequence represented as T_i ($i = 0$ represents idle and $i = 1$ represents busy). The duration of the idle and busy periods (T_i) is modeled to follow Generalized Pareto (GP) distribution as per [19]. DSA/CR system will perform spectrum sensing by observing the primary channel at a particular time duration known as sensing period T_s. After every spectrum sensing event, a binary decision is made based on various parameters of the channel depending on the spectrum sensing algorithms. A decision can either be $\mathcal{H}_0$ which represents the idle state or $\mathcal{H}_1$ which represents a busy state. Idle/busy duration can be estimated from the generated sequence. When a channel changes its state from idle to busy or vise-versa, the time interval $\hat{T}_i$ is calculated from last change which represents the estimation of the real T_i as described in Fig. 1(a) under PSS scenario but this scenario is not feasible in practice as errors are likely to occur. These errors can be classified as *false alarm* (P_{fa},idle state consider as busy) and *miss detection* (P_{md}, busy state consider as idle) as shown in Fig. 1(b). $\breve{T}_i$ represents the estimation of channel occupancy duration under ISS scenario as shown in Fig. 1(b) in which the impact of false alarm and miss detection is illustrated. These sensing errors are modeled as independent and identically distributed (I.I.D) random variables for each sensing event with a fixed probability of false alarm and the probability of miss detection. Here, P_{fa} & P_{md} are assumed to be constant with the value of 0.1.

The reliability of data is an integral part of any DL algorithm. Steps to generate data ($T_i, \hat{T}_i$, & $\breve{T}_i$) are similar to [4]. Here, $T_i, \hat{T}_i$, & $\breve{T}_i$ represents value of duration for which PU was active actually, under PSS and under ISS condition respectively.

III. Proposed Data Reconstruction Framework

LSTM-AE architecture is used to learn the representation of spectrum occupancy data under PSS condition and then sensing errors are detected in spectrum occupancy data under ISS condition. Detected errors are reconstructed using a simple RA.

A. Long-Short Term Memory Autoencoder

An autoencoder is a type of neural network which is trained to reproduce its input to its output [20]. In this paper, LSTM-AE is used because LSTM networks are designed to handle the sequential data and autoencoder architecture can learn the latent representation of the given data. Both together makes a state-of-the-art DL model that can learn the representation of sequential data. The internal structure of the LSTM unit can be found in [12].

LSTM-AE is typically trained in a way that DL model tries to recreate the input. As shown in Fig. 2, LSTM-AE is designed in a way that makes the recreation of data challenging by creating a bottleneck structure in the middle. In LSTM-AE architecture, first the encoder LSTM model reads the entire input sequence. After reading the whole input sequence, model represents an internal learned representation of the entire input sequence as a fixed-length vector. The fixed-length vector works as an input of the decoder model that interprets it as each step in the output sequence is generated. Fig. 2 describes the details of LSTM architecture.

B. Network Training

The training is implemented in python 3 using Keras API with Tensorflow [21] as backend. Data captured under PSS condition with total of 560,000 samples is splitted into 90/10 ratio as training and validation data keeping the duty cycle fix. PSS data is converted into LSTM input format i.e. *[batch_size, time_step, features]* with the time step (look-back factor) equals to 3. The model is built with iterative experiments and the final hyperparameters are given in the table III-B. Early stopping is used to halt the training procedure when validation loss become stable which works as a regularizer to avoid overfitting. It can be easily observed from the training and validation loss curves of Fig. 3 that model is perfectly fit.

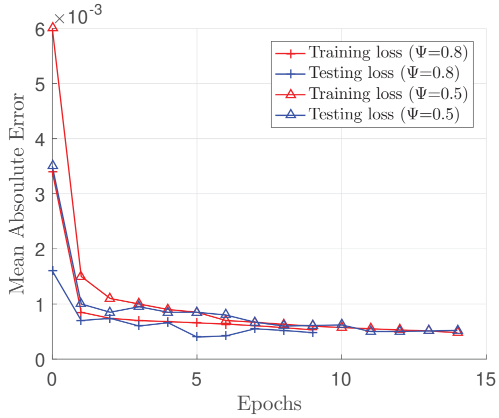

Fig. 3: Training loss and Validation loss for Ψ=0.8 and Ψ=0.5

Hyperparameters	Value
Initial learning rate	0.001
Batch size	32
Time step	3
Max epochs	15
Number of hidden layers	4
Optimization algorithm	Adam
Activation Function	ReLU
Loss Function	Mean Absolute Error

C. Sensing Error Detection

Error detection is a task of detecting outlier samples in the data. Firstly, the model is trained with the data generated under PSS condition. Then threshold is decided on the basis of distribution of mean absolute error (MAE) obtained from making predictions on training data and then calculating MAE by comparing with ground truth values. ISS data is given as an input to the model, as the model has learned the representation of PSS data, it will try to map the ISS data to PSS data. The output of model is compared with the original ISS data and MAE is calculated. After this, MAE of every ISS data sample is compared with threshold and the sample which has MAE higher than threshold is labeled as sensing error.

D. Proposed Reconstruction Algorithm

After detecting sensing errors in $\breve{T}_i$, indexes of error samples are extracted and provided to the RA described as Algorithm-1. Whenever a sensing error is detected due to false alarm or miss detection, it divides a single idle period into 3 periods, similarly, if K sensing error are detected in a single duration then, that one instance will be divided into $2K+1$ segment. Summing up this segment with the assumption that detected error is at the center point is one way to reconstruct the distorted distribution. The value of K has a significant impact on reconstructing the data as it decides the amount of surrounded values to sum up. Fixing the value of K is still a trial and error approach to get the optimal results. After correcting detected sensing errors, the method given in [4] is used to estimate the PAS and perform the analysis.

Algorithm 1: Proposed Reconstruction Algorithm

Initialize: $\tilde{T}_i = [\,]$; ▷ Empty list
Output: The reconstructed periods $(\tilde{T}_i)$
Input: The estimated periods under ISS $(\breve{T}_i)$,
MAE loss threshold (Threshold)
Trained LSTM-AE model (Model),
while $i \leq$ *no. of columns in* $(\breve{T}_i)$ **do**
  index = Model($(\breve{T}_i$[i]))
  j=1 ; ▷ Initialize j
  while $j \leq$ *len(index)* **do**
    if $(j+K)$ *in index* **then**
      if $(j+(2K+1)) \leq$ *len*$(\breve{T}_i[i])$ **then**
        $m = j$; ▷ Iterator
        while $m \leq (2K+1)$ **do**
          $\tilde{T}_i[j] = \tilde{T}_i[j] + \breve{T}_i[m]$;
          $m = m+1$;
        end
      else
        pass;
      end
      $j = j + (2K+1)$;
    else
      pass;
    end
  end
  $i = i+1$;
end

IV. Numerical Results

The performance of the proposed method is evaluated by the means of simulations. As discussed in section-II, data follows GP distribution with parameters such as location (μ_0) 10, Scale (λ_0) 30, and Shape (α_0) 0.25. From Fig. 4, we can observed that the relative error decreases significantly from 80% to 9%, when the mean is estimated from the reconstructed data. An important thing to notice here is that, relative error remains nearly constant regardless of any sensing time T_s, even for the $T_s < \mu_i$. Whenever a sensing error occurs, it divided the period but the sum of divided periods remains constant. Proposed RA use this fact and summed up the surrounded K value from the index of detected sensing error. Due to this summation, distorted period are reconstructed and relative error in mean decreases. This also indicates that the LSTM-AE has been able to detect sensing errors effectively and it is generalized well over the training data.

The comparison of distribution of reconstructed data and original data is performed using the classic Kolmogorov-Smirnov (KS) distance [22]. Here, $F_{T_i}(T_i)$ is in continuous domain, while $F_{\tilde{T}_i}(\tilde{T}_i)$ is in discrete domain. Since it is not possible to compare continuous and discrete domain directly, interpolation is used to convert $F_{\tilde{T}_i}(\tilde{T}_i)$ in to continuous domain represented as $F_{\tilde{T}_i}(T_i)$. Fig. 5 compares the KS distance of the proposed framework with the KS distance resulting from the direct estimation under ISS scenario. The improvement of the proposed framework can be assessed by the fact that KS distance has decreased significantly. The proposed RA is dependent on the input from the LSTM-AE i.e. the index values of detected sensing errors. Due to this, RA can miss the

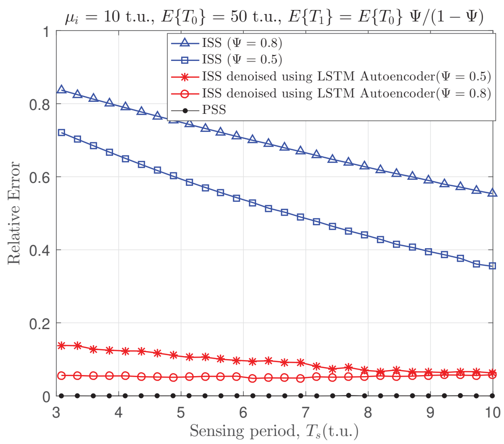

Fig. 4: Relative error of the estimated mean idle period $E\{\breve{T}_0\}$ as a function of the sensing period T_s

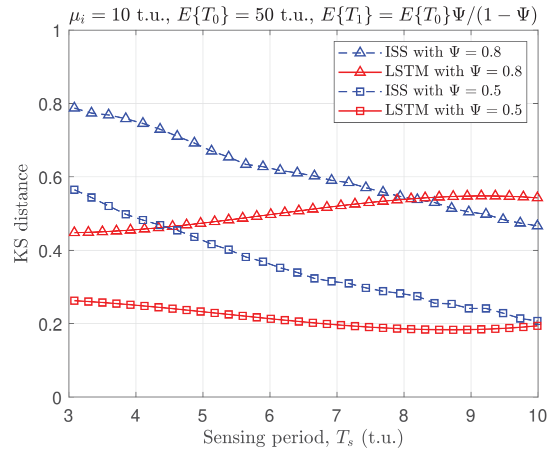

Fig. 5: Estimation error of the distribution of idle periods $F_{\breve{T}_0}(kT_s)$ as a function of the sensing periods T_s

sensing errors which are not detected by the LSTM-AE. It can be observe that for $T_s = 3$ we get ∼35% gain and for $T_s = 5$ we get ∼20% gain in estimation accuracy. As the sensing time T_s increases, the ability of the system to detect state change for duration less then T_s decreases. This causes hindrance in detecting sensing errors for LSTM-AE at higher T_s. From Fig. 5, it can be easily observed that proposed framework leads to a significantly improved accuracy in the estimation of the original distribution for $\Psi = [0.5, 0.8]$ for $T_s < 8$ t.u. without requiring any prior knowledge of PU activity statistics.

V. Conclusions

This paper has addressed the problem of accurately estimating the PAS under ISS condition by proposing a deep learning-based LSTM-AE approach to detect sensing errors and a simple RA to correct them. The performance has been evaluated using computer simulations. We notice that the LSTM-AE has been effective in learning the latent representation of the data and use this learning to detect sensing errors. The proposed RA is effective in correcting sensing errors in single iteration. With the proposed framework, relative error of estimated mean decreases from 80% to 9%. The proposed schema has significantly improved the estimation of PAS without requiring any prior knowledge of PU activity statistics to reconstruct the data, making it practically implementable.

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