Chapter 18
Enhancing Cooperative Spectrum Sensing in Flying Cell Towers for Disaster Management Using Convolutional Neural Networks

M. Suriya and M. G. Sumithra

18.1 Introduction

Disasters are impromptu events that not only cause significant damage or loss of life but may also hammer out the existing communication networks. The damage caused to the networks along with increased demand in traffic hampers towards the recovery effort. Studies show that spectral utilization is relatively low when examined not just by frequency domain, but also across the spatial and temporal domains. Thus, an intelligent device that is aware of its surroundings and able to dynamically adapt to the existing radio frequency (RF) environment by considering is capable of utilizing spectrum more efficiently and dynamically by sharing spectral resources. Post disaster requires restoration of telecommunications in order to enable first responders to coordinate their responses, and make all affected public to access information and contact friends and relatives [1].

The unmanned aerial vehicles (UAVs), also known as drones, are adapted widely for wireless networking applications. UAVs can be used as flying cell towers, i.e. they are mounted with base stations to enabling communication to wireless networks by providing coverage, reliability and energy efficiency. UAVs can be deployed in order to complement existing cellular systems during post disaster scenario by providing hotspot and network coverage. These devices must be capable enough to operate by adapting to the environment and provide communication. A cognitive radio (CR) is an intelligent device capable of observing the environment and reconfigure based on the surrounding by learning from its experience. This work utilizes the CR technology for disaster responsive and relief networks and makes them as intelligent responsive networks. This work primarily proposes a

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deep learning based technique called SpecCNN to improve spectrum sensing by calculating the signal-to-noise ratio in the CR adapted UAVs for any disastrous scenario [2].

The remaining part of the chapter is organized as follows: Feasibility study based on the proposed works is done and is presented in Sect. 18.2. Section 18.3 presents the system model for intelligent disaster response networks. The deep learning based technique called convolution neural network for cooperative spectrum sensing (CSS) is presented in Sect. 18.4. Section 18.5 covers the proposed SpecCNN model for emergency cognitive radio. The results of the work are provided in Sects. 18.6, and 18.7 concludes the chapter.

18.2 Literature Survey

Namuduri in [3] has devised and deployed an aerial communication system that uses AR200 drone mounted with a base station that is weighing about 2 kg. This cell tower works in Band 14 (public safety band) and helps to restore cellular service in the disastrous affected location and also allows share photos and video among communicating users. This innovative public safety responder system provides reliable communication when the coverage is increased as the drone flew higher.

Islam and Shaikh [4] have proposed a disaster management system based on dynamic cognitive radio network technology. In this Artificial Neural Network (ANN) technique was devised for disaster detection based on backward propagation algorithm. He also created a service discovery scheme along with ANN-based spectrum sensing for performing coordination during the time of disaster. The switching time of spectrum sensing scheme was also analysed by calculating the latency of proposed service discovery scheme.

In [5] Grodi et al. work the importance of communication links and its role during any emergency scenario was highlighted. When public telephone networks damaged during disaster, Unmanned Aerial vehicles (UAVs) were used to establish communication between those persons met with an emergency and the rescue team. It explains the use of drones to act as mobile base stations and route wireless communication to the nearest working public telephone network access point.

Mozaffari et al. in [6] explore features of unmanned aerial vehicles such as mobility, flexibility, and its adaptive altitude and suggest the utilization of drones for various wireless systems applications. The work explains how UAVs are deployed as flying mobile terminals by providing additional capacity to hotspot areas and also to enhance network coverage in emergent public safety situations. Also introduces various tools such as optimization theory, machine learning, stochastic geometry, transport theory, and game theory for addressing UAV problems.

Lee et al. in [7] investigates the cooperative spectrum sensing (CSS) in a cognitive radio network (CRN) which consists of multiple secondary users (SUs) at a point where they cooperate to detect when a primary user (PU) arrives. The concept of deep sensing is proposed by utilizing convolutional neural network (CNN). The sensing samples are trained using CNN instead of traditional mathematical model. The results of the work show a significant increase in places where there is low signal-to-noise ratio (SNR) when the number of training samples were sensible and thus proposed an environment aware CSS.

18.3 Intelligent Disaster Response Networks

During natural disaster lot of damage is caused to the telecommunication networks leading to loss of communication among people who are in affected zone and require emergency communication. This rises to build a temporary relief and response system to support communication in places where available telephone network is destroyed. The unmanned aerial vehicles also called drones can help this kind of disastrous scenario by making it mount with a base station weighing about 2 kg and route to nearest public telephone network access point. Figure 18.1 illustrates the deployment of drones as aerial base stations (BSs) to deliver a reliable, cost-effective, and on-demand wireless communications over disaster affected areas. These devices are called as flying cell towers as they can coexist and connect with terrestrial cell towers as long they are deployed in the air. The advantage of these flying cell towers is their ability to establish better line-of-sight (LoS) communication links to the ground users compared to conventional system [8].

The use of dynamic learning algorithms enable drones to effectively adjust their movement, flight path, and motion control to service their ground users. UAVs adapt to any environment dynamically in a self-organizing way and autonomously optimize their trajectory. The training of these dynamic devices using advanced neural networks and performing data analytics will make predict ground user behaviour to track user mobility and thereby effectively operate drones. This feature

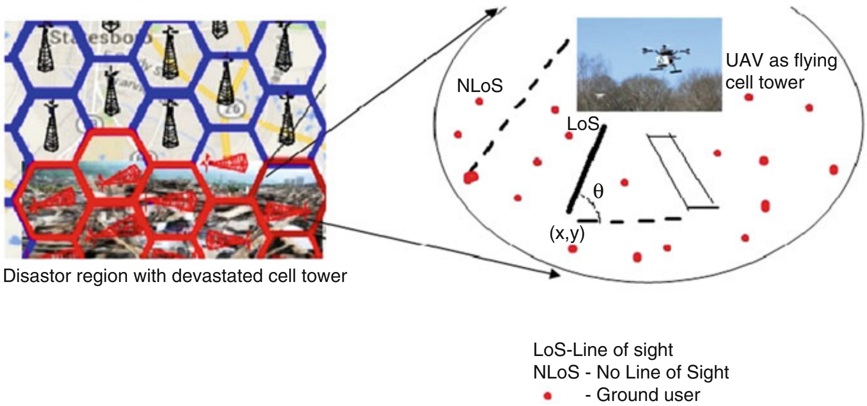

Fig. 18.1 Depiction of intelligent flying cell towers at disaster prone location

helps in designing a special cache enabled UAV system to store users' mobility pattern and dynamically optimize the trajectory to enhance communication [13].

18.4 Deep Learning for CSS Using CNN

In [9] a cognitive radio network (CRN), the process of spectrum sensing, helps to identify the presence of primary user when there are multiple secondary users allocated to the available frequency spectrum. The most challenging task in CRN is identifying the tolerable level of all PUs in the network which requires an efficient utilization of spectrum sensing mechanism. Compared to conventional learning techniques deep learning is gaining attention and is being used for many applications such as natural language processing, image processing and various analytical applications. Due to efficient learning process and data support it is widely used for a number of big data applications. A deep neural network (DNN), in Fig. 18.2, consists of more than two hidden layers, hence called multi-layer network that emulate the working of human brain neuron system. Convolutional neural network (CNN) and recurrent neural network (RNN) [10] are used to train huge amount of sample data that requires complex mathematical modelling.

Cooperative communication primarily increases the coverage and minimizes the outage of wireless links for certain channel conditions [11, 12]. DNN has been proposed to wireless communication systems to classify signals where multiple SUs are present in a cooperative spectrum sensing scheme. The CNN technique is applied in spectrum sensing by considering each **SUs** sensing results as training sample and combining the results to predict **PUs** efficiently. When CNN is applied to CSS, the sensing results are optimized by combining the movement of PU and location of SU to enhance spectrum sensing.

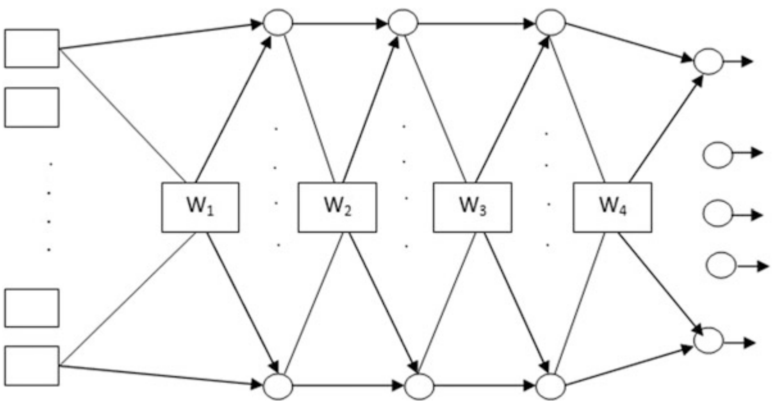

Fig. 18.2 Deep neural network model with three hidden layers

18.5 SpecCNN Model for Emergency Cognitive Radio

18.5.1 Cyclostationary Signal Feature Extraction

Figure 18.3 depicts how the feature extraction process is performed over the cyclostationary signal (PU) to separate the noise signal and extract different features of the signal to perform spectrum sensing.

A scenario of CRN composed of one PU and multiple secondary users (SUs) can be represented as a binary hypothesis-testing. The following basic hypothesis H_0 and H_1 are considered as in Eqs. (18.1) and (18.2).

H_0: Power of primary user absent at time 't'
H_1: Power of primary user present at time 't'

$$H_0 : \quad x(t) = n(t) \tag{18.1}$$

$$H_1 : \quad x(t) = h(t) + n(t), \quad t = 0, 1, \ \ldots, N - 1 \tag{18.2}$$

where

N = number of samples over a period of received signal
$x(t)$ = secondary users signal
$h(t)$ = primary users signal
$n(t)$ = amount of AWGN noise (Additive White Gaussian Noise) with variance σ_n^2.

The PU signal and noise can be distinguished by extracting the different feature of the cyclostationary signal (PU). Suppose that the SU receives the signal is $h(t)$, and its cyclic autocorrelation function can be represented in Eq. (18.3).

$$R_x^\alpha = \frac{1}{T_0}\int_0^{T_0} R_x\,(t,\tau)\,\mathrm{e}^{-j2\pi\alpha t}dt \tag{18.3}$$

where α = cyclic frequency and T_0 = cycle period.

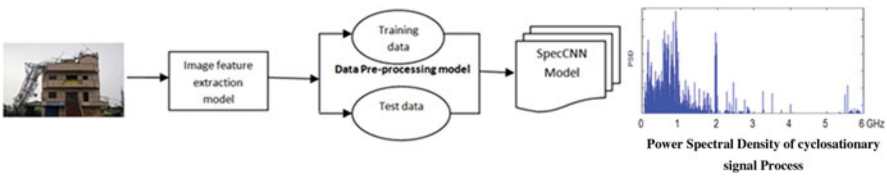

Fig. 18.3 Feature extraction process

The cyclic autocorrelation function is obtained by Fourier transform, and the spectral correlation function (SCF) is obtained as a Fourier transform relation between the conventional power spectral density and the autocorrelation given in Eq. (18.4).

$$S_x^{\alpha}(f) = \int_{-\infty}^{\infty} R_x^{\alpha}(\tau)\, \mathrm{e}^{-j2\pi f\tau} d\tau \tag{18.4}$$

where

$S_x^{\alpha}(f) =$ power spectral density
$R_x^{\alpha}(\tau) =$ autocorrelation function

Based on the binary hypothesis-testing function the (1) autocorrelation function, (2) SCF function and (3) energy function of the extracted signals are obtained as in Eqs. (18.5) and (18.6), respectively.

$$R_x^{\alpha} = \begin{cases} R_{x,0}^{\alpha}, & H_0 \\ R_{x,1}^{\alpha}, & H_1 \end{cases} \tag{18.5}$$

where

$H_0 = R_{x,\,0}(t,\tau)\mathrm{e}^{-j2\pi\alpha t}$
$H_0 = R_{x,\,1}(t,\tau)\mathrm{e}^{-j2\pi\alpha t}$

$$S_x^{\alpha}(f) = \begin{cases} S_{x,0}^{\alpha}(f), & H_0 \\ S_{x,1}^{\alpha}(f), & H_1 \end{cases} \tag{18.6}$$

where $H_0, H_1 = \rho_n^2\ \sigma(\alpha)$, since white Gaussian noise.

The energy feature of the extracted signals is obtained as in Eq. (18.7).

$$E_{\mathrm{e},x} = \begin{cases} E_{\mathrm{e},0}, & H_0 \\ E_{\mathrm{e},1}, & H_1 \end{cases} \tag{18.7}$$

where

$H_0 = \sum_{t=1}^{N}(n(t))^2$
$H_1 = \sum_{t=1}^{N}(h(t)+h(t))^2$

Once the features are extracted, the data is pre-processed to make the training data set and the test data set standard.

18.5.2 SpecCNN Algorithm

Deep sensing CNN is utilized to analyse the presence of PU signal by combining all the individual sensing results by exploring the signal spectral features based on the amount of noise signal. A spectral image is fed as input to neuron for each sensing result and the CNN performs identification of spectral correlation using adjacent pixels since each image has interrelated spectrum spatial relationship. In Fig. 18.4, a CNN model consists of convolution part (Conv) at the front and fully connected (FC) part at the back. The convolution part extracts features and passes data to the rectified linear unit (ReLu) layer which helps in making system non-linear, and the output of ReLu is fed to the max-pooling layer that generates max(x, 0) when input is x. This layer helps in reducing the size of the data without any loss in the actual input. The FC layer makes final decision with input from the Conv layer and its output fed to softmax function to detect the presence of PU signal or not.

18.5.2.1 SpecCNN Training Algorithm

1. Calculate the output α^i at each neuron during forward propagation.
2. Calculate error δ^i at each neuron during back propagation.
3. Compute weight from neuron i to j as gradient weighted value ω^{ij}.
4. Apply gradient descent rule to update weight:

$$\delta^i = \phi\left(\omega^{ij}\mathrm{Conv}\left(x^{ij}\right) + b^i\right)$$

where

Φ = activation function of output i
ω^{ij} = weighted sum at output i
b^i = bias/error at i

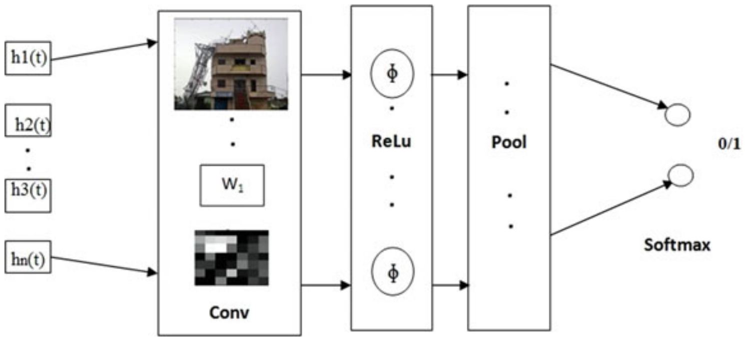

Fig. 18.4 SpecCNN model

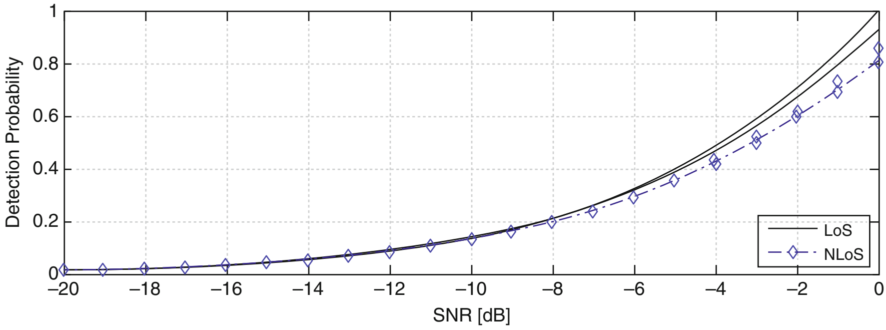

Fig. 18.5 Signal-to-noise ratio vs. detection probability for Los and NLoS

The above proposed SpecCNN model performs computation to verify the presence or absence of PU signal which is considered as index 1 and 0, respectively. Input signal of two-dimensional matrix (2 × 2) is considered that includes cyclostationary and energy signal. The convolution layers considered for the network includes a filter size (3 × 3), stride 1 and padding = 0. The gradient descent stochastic technique is used to train the neurons in each layer.

18.6 Evaluation and Discussion

The proposed SpecCNN model for efficient spectrum sensing based on CNN is simulated in MATLAB environment using AWGN channel for 100 samples at a carrier frequency of 10 Hz. The cyclostationary signals are calculated at an SNR value of −15 dB and SCF is extracted using Eq. (18.6) and the energy features are extracted using Eq. (18.7). The resulting data are used as training set to perform CNN process as discussed in the proposed SpecCNN algorithm for training the network and updating weights. The probability of signal detection with a false alarm $P_{\mathrm{f}} = 0.05$ (see Fig. 18.5) that shows the rate of PU and SU increases with the decrease in SNR value. The amount of interference of cyclostationary signal for the number of users $m = 1$, $m = 10$ and $m = 100$ for evaluating primary signal spectrum is analysed (see Fig. 18.6).

18.7 Conclusion

The emerging problem of spectrum sensing was considered for disastrous affected areas when a drone deployed the cell tower and acted as flying cell tower. The cooperative spectrum sensing using cyclostationary signal based image feature extraction was implemented using the proposed SpecCNN deep learning algorithm

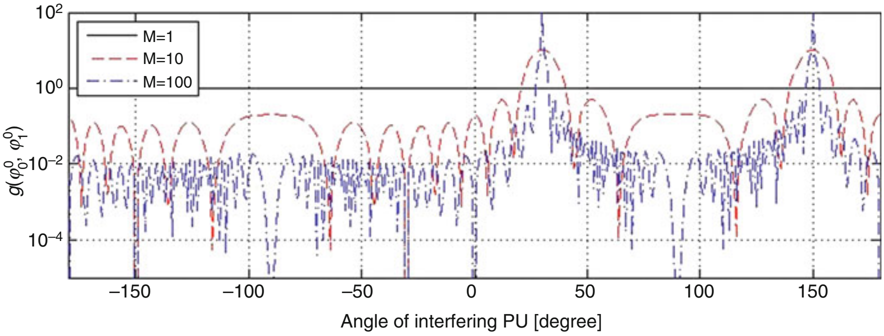

Fig. 18.6 Rate of interference of PU signal

model and the test accuracy of 0.9068 (training rate 300) was obtained, which indicated the detection probability increased in the minimal SNR region with the deep learning model of spectrum sensing.

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