Computer Vision and Bi-directional Neural Network for Extraction of Communications Signal from Noisy Spectrogram

Seksan Phonsri, Sankha Subhra Mukherjee, and Mathini Sellathurai
Institute of Sensors, Signal and System
Heriot-Watt University
Edinburgh, United Kingdom EH14 4AS
{SP318, SM794, and M.Sellathurai}@hw.ac.uk

***Abstract*—Extraction of communication signals from noisy spectrograms is a challenging problem which has not been explored extensively from an intelligent signal processing and computer vision based perspective. In this paper we propose a novel technique of extracting the communications signal from a noisy spectrogram using a combination of fuzzy neighborhood thresholding based self organizing neural network and morphological operations. We show that about 98% detection is achieved at 5% false alarm of a particular scenario outperforming traditional energy detection.**

Keywords—Computer Vision; Spectrogram; Bi-directional Self-organizing Neural Networks; Fuzzy Hostility Index; Morphological Filtering; Blob Detection;

I. Introduction

The most commonly used spectrum sensing algorithms in literature are energy detectors, covariance/eigenvalue based signal detectors and regulatory detectors such as feature detectors and matched filter detectors [1]. Although attractive because of their simplicity, energy detectors present a series of drawbacks including poor performance in low SNR settings as well as being seriously weakened by uncertainties in the device's parameters, e.g. the background noise variance. In noise uncertainty and low SNR scenarios, they are not as good as regularity detectors or match filters for detecting the signal content at a low SNR. Since the regularity detectors and match filters all require prior information about the nature of the signal, they cannot be applied in an arbitrary scenario. Covariance or eigenvalue based spectrum sensing such as techniques are blind in the sense that they do not require knowledge of the noise variance or any other signal patterns whereas these techniques are significantly more complex to implement in real-time compared to energy detectors [2].

In this context, Smith et al. proposed computer vision techniques as in [3] to significantly increase the performance of energy based spectrum sensing method by exploiting the signal compactness in the time-frequency plane to extract noisy signals which is a blind energy detector, i.e., an energy detector without a priori knowledge of noise variance. In this paper, we further improve this algorithm first by introducing a novel auto-thresholding of the image using statistical properties of the STFT image in contrast to [3] which just defines a threshold value as mode +4dB. Since the determination of thresholding with mode +4dB is quite arbitrary and does not always produce good results, here we exploit the auto-thresholding with more principle for generating a binary image.

Secondly, we introduce a bi-directional self-organizing neural network (BDSONN) to automatically clean up the noise after auto-thresholding which helps the subsequent connected component extraction in the time-frequency domain just using local points. Since the threshold is computed on the global histogram statistics of the spectrogram, it often leaves a lot of noise in some regions that can arise due to the time varying nature of the noise and signal strength. The BDSONN works on extracting local fuzzy information in the image for better estimating signal from noise. The BDSONN has proven to be very effective in extracting objects in noisy images [4]. It does not require prior training but works using local fuzzy information. This makes it a very good candidate in very general noisy scenarios. The adaptability of the BDSONN to a vast range of scenarios is what motivated us to use it in the first place. This proposed method further improves performance particularly at low false alarm rates compared to [3].

II. Proposed Algorithm

The standard technique of spectrum sensing employing energy detector in a wideband scenario uses Neyman-Pearson test (NPT) to every frequency bin in the STFT:

$$\frac{\Pr(r|H_1)}{\Pr(r|H_0)} > \tau, \qquad (1)$$

where $\Pr(r|H_1)$ is the likelihood of signal being present along with noise and $\Pr(r|H_0)$ is the likelihood of only noise being present in observation r. If the ratio is greater than a threshold value (τ) then a detected signal is classified. The threshold can be estimated using an adaptive estimation over time. This test is generally applied to every frequency bin of the short time

This research was supported by a grant from the Defence Science and Technology Laboratory (DSTL).

978-1-4673-9149-8/15/$31.00 ©2015 IEEE

Fourier transform (STFT) of the signal to detect signal presence. As noticed in [3], this technique however ignores the time-frequency compactness of the communication signals. Since communication signals in general are designed to be compact in time and frequency domain, it means that the probability of detecting signal is higher if the adjacent bins of a STFT have signal present.

In contrast to the above traditional energy detection test, here first we analyze the signal compactness in time-frequency plane by representing the signals spectrograms as inverted grayscale images where darker pixel values represent higher signal content. The method proposed in this paper consists of four parts: (1) determination of automatic threshold value from spectrogram grayscale image, (2) cleaning up threshold noise using local information using BDSONN, (3) application of morphological filters and (4) blob detection for classifying the detected signals, according to block diagram in Fig. 1.

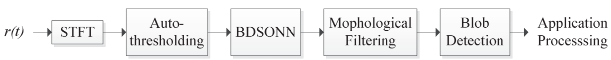

Fig. 1. Workflow block diagram.

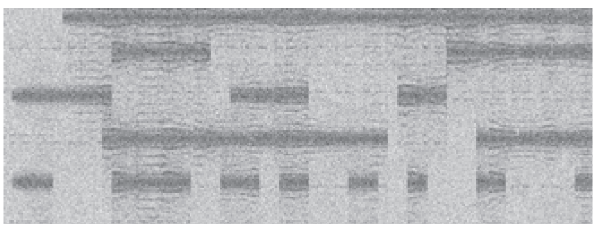

Fig. 2. Noisy spectrogram. Darker regions are signals. SNR = -5dB.

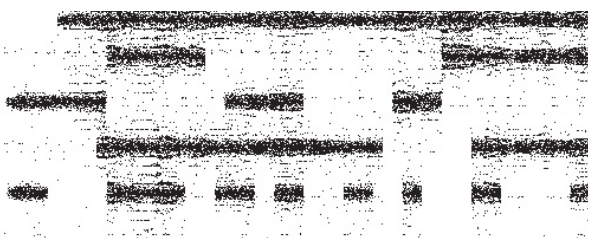

Fig. 3. Effect from auto-thresholding of Fig. 2.

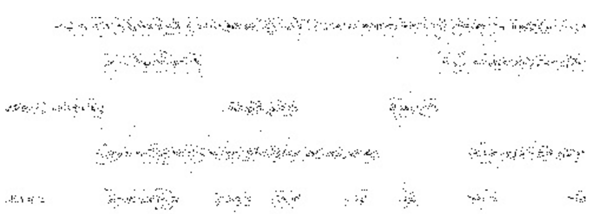

Fig. 4. Effect of thresholding using mode+4dB prescription proposed in [3].

A. *Automatic Threshold Detection*

To detect the signals, the first step performed is converting the grayscale spectrogram to a binary image. To get consistent performance, the threshold value is automatically determined using the following technique. Firstly, a global threshold (α) is determined by calculating the image mean (μ) and subtracting the standard deviation (σ) from it, according to (2), (3) and (4) respectively. This reduces the signal to significant components, and low magnitude noise is eliminated. Fig. 2 shows the original signal spectrogram in presence of noise. Fig. 3 shows the result of auto-thresholding method proposed in this section. Fig. 4 contrasts the result of thresholding with mode +4dB proposed in [3] on our test signal.

$$\mu = \frac{\sum_{I(x,y)} I(x,y)}{N} \tag{2}$$

$$\sigma = \sum_{I(x,y)} (I(x,y) - \mu)^2 \tag{3}$$

$$\alpha = \mu - \sigma \tag{4}$$

B. *Bidirectional Self-Organizing Neural Network*

For this application, the specific network was proposed by Bhattacharyya et al. as in [4]. This network relies on building a local fuzzy context sensitive thresholding to extract objects. The proposed self-supervised bi-directional three layer neural network (BDSONN) architecture is the fully connected 2D feedback neural network architecture. It consists of an input layer, an intermediate layer and an output layer of neurons. The number of neurons in each of the network layers corresponds to the number of pixels in the input image. The fuzzy membership values of the input image scene are fed as input to the input layer. The neurons in each layer of the network are connected to each other within the same layer with full and fixed intra-layer interconnection strengths. Each neuron in a particular layer of the network is connected to the second order neighbors of the corresponding neuron in the previous layer following the second order neighborhood-based topology. For the network operation, the fuzzy hostility index (ζ) defined over all the input image pixels is computed as follows:

$$\zeta = \frac{3}{8} \sum_{i=1}^{8} \frac{|\mu_p - \mu_{qi}|}{|\mu_p + 1| + |\mu_{qi} + 1|} \tag{5}$$

where μ_p denotes the fuzzy membership value of pixel p and μ_{qi} means the membership value of the i^{th} neighbor in the 2^{nd} order neighborhood. This shows that the lower the hostility index, the higher the homogeneity of the neighborhood. Fig. 5 exhibits the intra-layer computation of local fuzzy hostility index. The initial fuzzy membership value for the input layer is initialized to the pixel grayscale values scaled to the inclusive range of 0-1 floating point numbers.

The inter layer interrelationship weights (w_{kilj}) between i^{th} neuron in k^{th} layer and j^{th} neuron in l^{th} layer for forward propagation are defined as

$$w_{kilj} = \left| \mu_{lj} - \mu_{ki} \right| \tag{6}$$

Thus, the forward propagation to the next level is defined as

$$I_{lj} = \sum_i w_{kilj} \times I_{ki} \tag{7}$$

The output O_j of the neuron is provided by

$$O_j = f(I_{lj}, \beta), \tag{8}$$

where f stands for a beta activation function defined as

$$f(t) = \int K x^{\alpha} (1-x)^{\beta c} \, dx, \tag{9}$$

where the parameter β denotes the fuzzy cardinality estimate of the neighborhood. Fig. 6 shows the inter-layer propagation of the network architecture. The choice of the thresholding parameter for the activation function helps in incorporating the image heterogeneity information in the operational characteristics of the network architecture, which otherwise, would be lacking if a single point fixed thresholding parameter is chosen. As a result, noise immunity and generalization capability are induced in the network architecture. One input and 2 cycle-iterations are performed using the BDSONN. Fig. 7 and 8 present the result of BDSONN processing on the output of Fig. 3 with 1 and 4 iterations, respectively.

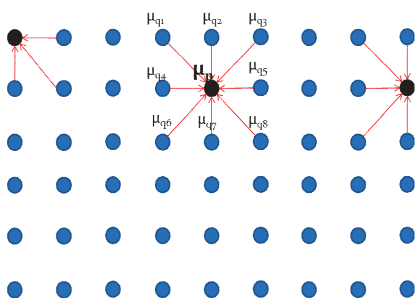

Fig. 5. Intra-layer fuzzy hostility index computed according to (5).

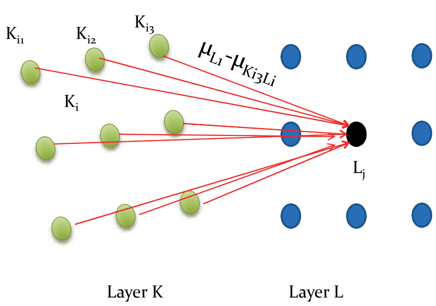

Fig. 6. Inter-layer weight according to Eq. (6) and propagation dynamics according to Eq. (7), (8) and (9), respectively.

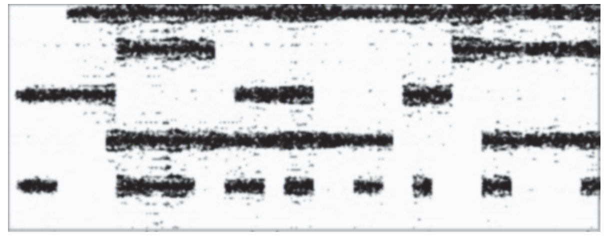

Fig. 7. After one stage of BDSONN processing.

Fig. 8. After four stages of BDSONN processing.

The BDSONN determines the neighborhood homogeneity based on local fuzzy membership values and the fuzzy hostility index of the neighborhood. This shows that the higher the noise in the neighborhood, the higher the fuzzy hostility index of a given pixel. Hence iteratively, it tries to merge the homogeneous regions and reduce the noisy regions. When it converges, it provides a better estimate of signal region from noise. This creates a better signal mask for the spectrogram that needs very little clean up when using morphological operations. In addition, since it is a fully connected network in a single layer, the object mask extraction works for any arbitrary shape of object, whereas rectangular morphological operations like opening and closing introduce a lot of horizontal and vertical false alarms.

The computational cost imposed by the network is pretty low and can be implemented in real-time systems. Furthermore, the network computations can be easily parallelized on massively parallel SIMD processors for additional speedup. Since the network is very general and no prior training is required, it can work on various kinds of noise and corruption present in the signal spectrogram. This is specifically true compared to using supervised networks, which must be trained for different kinds of noise, for noise elimination at various SNR levels [5]. The network is also quite robust even in presence of high amount of noise.

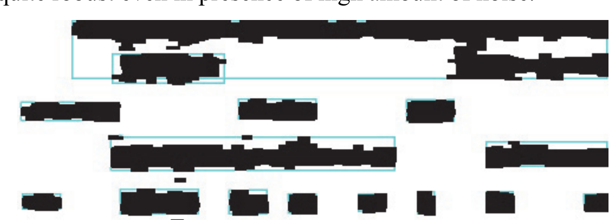

Fig. 9. Final output after morphological filtering and blob detection.

C. Morphological Filtering and Blob Detection

The obtained images from employing the BDSONN technique may have the rough contours. The morphological filtering will be applied to smoothen out the bumpy contours on binary or grayscale images using various morphological kernels. This technique is employed for several objectives related to representing and extracting shapes in the image as well as smoothing and filtering boundaries in an image as well. Mathematical morphology is based on an algebraic non-linear system with the better performance on elimination of pulse noise and white noise, and composed of two basic techniques that are erosion and dilation. For this processing we follow the algorithm presented in [3]. The kernel used for opening the image is a 3×5 structural element and the one used for closing it subsequently is a 3×7 structural element. The operations are standard operation where the closing operator is used for closing the small gaps in image and the opening operator is used to remove stray signals.

Finally, the blob detection algorithm encourages the morphological filtering technique in visually inspected application in order to increase the capability of detection more precisely. Blob detection is usually composed of foreground mask extraction, foreground mask correction and blob segmentation through connected element classifying. In this place, foreground mask means a crowd of extracted foreground pixels. There may be gaps occurring in the foreground mask resulting in some foreground pixels may not be extracted during the process of foreground mask extraction. Such a foreground mask needs to be reformed via eliminating isolated pixels or jutted pixels and filling up gaps [6]. Fig. 9 illustrates the final output of the algorithm after morphological opening and closing and subsequent blob detection.

III. RESULTS

In order to compare the performance of the proposed algorithm to the others, we use the same signal scenario given in Fig. 1 as in [3]. Fig. 10 depicts the detection performance of the proposed algorithm, the adaptive threshold explained in the outset of Section II and the baseline method [2] in a graph which plots the detection rate P_d against the false alarm P_{fa}.

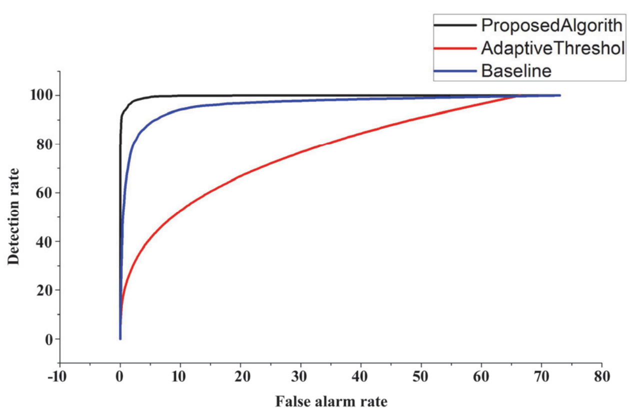

Fig. 10. Plot of detection rate in % against false alarm rate for test signal in Fig. 2. The computer vision techniques have been compared to the Adaptive Neyman-Pearson-hypothesis-testing and Baseline method.

It is to be noted that the proposed algorithm significantly improves the detection performance for the same amount of false alarm. For the test signal in Fig. 1 as in [3], the proposed algorithm generated an auto-thresholding of 154 gray-level and a corresponding false alarm of 5.4% with 98.27% accurate detection. Fig. 11 depicts the masked original signal being extracted from the original signal without noise. This original mask is used in the experiment to compare the performance of all the algorithms.

Fig. 11. Original signal mask is classified.

IV. CONCLUSION AND FUTURE WORK

In this work we have used computer vision techniques and BDSONN for spectrum sensing using energy detectors with no a priori knowledge of noise variance. We improved upon previous work in the direction of [3]. However, it must be pointed out that further study will benefit the work to determine the effects of other morphological kernel sizes and other kinds of activation functions for the BDSONN. Moreover, the resolution of STFT cannot be arbitrarily small in both time and frequency components. Thus, there is always a tradeoff associated with using STFT which can be solved using multi-resolution transforms which will allow this technique to be applied even more fine-grained application and higher noise scenarios.

REFERENCES

[1] B. Zayen, W. Guibene, D. Panaitopol and A. Hekkala, "Specification of signal classification techniques for cognitive radios," EURECOM, Sophia Antipolis, Nice, France, April 2012.

[2] A. Kortun, T. Ratnarajah, M. Sellathurai, C. Zhong and C. B. Papadias, "On the Performance of Eigenvalue-Based Cooperative Spectrum Sensing for Cognitive Radio," *IEEE Journal of Selected Topics in Signal Processing*, vol. 5, no. 1, pp. 49 - 55, Feb. 2011.

[3] C. Smith, Q. R. Black and M. Magee, "Computer vision for improved single-sensor spectrum sensing," in *International Conference on Sensor Signal Processing for Defence (SSPD)*, London, Sept, 2012.

[4] S. Bhattacharyya, P. Dutta and U. Maulik, "Binary object extraction using bi-directional self-organizing neural network (BDSONN) architecture with fuzzy context sensitive thresholding.," *Journal of Pattern Analysis and Applications*, vol. 10, no. 4, pp. 345 - 360, May 2007.

[5] S. Mukherjee, R. Chowdhury and S. Bhattacharyya, "Image Restoration Using a Multilayered Quantum Backpropagation Neural Network," in *International Conference on Computational Intelligence and Communication Networks (CICN)*, Gwalior, Oct. 2011.

[6] T. B. Nguyen and S. T. Chung, "An Improved Real-Time Blob Detection for Visual Surveillance," in *International Congress on Image and Signal Processing (CISP)*, Tianjin, Oct. 2009.