Proceedings of the Sustainable Research and Innovation Conference
JKUAT Main Campus, Kenya
6 - 7 October, 2021

Automatic Modulation Classifier Based Spectrum Sensing in the context of Cognitive Radio

E.Mureu, P. Kihato and P. Langat

***Abstract*—**Cognitive Radio (CR) is one of the technologies that promises to enhance the spectral efficiency, by having secondary users access channel(s) allocated to a primary user but are idle in a given area or time. Spectrum sensing is one of the key functionalities of the CR system that detects channels that are occupied by the primary users so that secondary users could avoid them in-order not to cause harmful interference.

Many spectrum sensing methods have been proposed in the literature, each with its own merits and demerits. The main demerits for most of them is, either the need for prior knowledge of the primary user signal, or poor performance in the face of low Signal to Noise Ratio (SNR).

The aim of this study was to develop a spectrum sensing method that has the ability to detect the presence of unknown signal in a channel, even under moderately low SNR using an Automatic Modulation Classifier (AMC) based on the Convolution Neural Network (CNN). The logic behind the use of the proposed classifier is the fact that today, every wireless communication system makes use of some form of modulation scheme. Therefore, a detection of a signal with a given modulation scheme would imply the presence of a primary user signal in that channel. If no signal with a known modulation scheme is detected, then it could be concluded that the channel is idle and could be used by secondary users.

Using MATLAB, synthetic channel-impaired waveforms were generated for eight digital and three analog modulation schemes. Using the generated waveforms, a six-layer CNN was trained, validated and tested. The trained CNN was then used as an AMC, to classify input signals according to their modulation type. The proposed classifier was able to attain up to 100 % classification accuracy for some of the modulation types with an average accuracy of 95.3% for an SNR of 30dB. The obtained results showed that the proposed classifier was able to recognize modulation type of the input signals and hence identify the occupied and the unoccupied channels. Therefore, it could be used for spectrum sensing in the context of cognitive radio.

Keywords: Automatic Modulation Classifier, Cognitive Radio, Convolution Neural Network, Signal to Noise Ratio, Spectrum Sensing.

I. Introduction

THE popularity of wireless communication has continued to put a big strain on the available radio spectrum as more and more applications are developed. The result of this, is scarcity of radio spectrum to support new wireless applications as most of it has already been allocated. But from the spectrum occupancy measurements that have been conducted around the world, it has been found that a good chunk of the allocated radio spectrum remains idle [1][2][3][4] and [5]. Therefore, these studies have shown that the scarcity of the radio spectrum has more to do with the approaches used to allocate and access the spectrum as opposed to its over utilization [6].

Therefore, there is need for more innovative ways to allocate and manage radio spectrum to address this artificial shortage. The cognitive radio system is one such innovation [7]. A Cognitive Radio System (CRS) is defined as a radio system employing technology that allows the system to obtain knowledge of its operational and geographical environment, established policies and its internal state; to dynamically and autonomously adjust its operational parameters and protocols according to its obtained knowledge in order to achieve predefined objectives; and to learn from the results obtained. CRS makes it possible for devices to use radio spectrum on opportunistic and secondary basis, on condition that they don't cause harmful interference to the primary users.

One of the key functionality of the CRS is the spectrum sensing that allows the system to obtain knowledge of its operational and geographical radio environment. A number of spectrum sensing methods have been proposed, each with its own merits and demerits [7]. The main demerits for most of them is, either the need for prior knowledge of the primary user signal, or poor performance in the face of low Signal to Noise Ratio (SNR). The aim of this study was to develop a spectrum sensing method that has the ability to detect the presence of unknown signal in a channel, even under moderately low SNR.

Riding on the fact that, today, every, wireless communication system make use of some form of modulation scheme, a detection of a signal with a given modulation scheme would imply the presence of a primary user signal in that channel. If no signal with a known modulation scheme is detected, then it can be concluded that the channel is idle and can be used by secondary devices. This brings us to the realm of Automatic

F. A. *E. W. Mureu, Department of Electrical and Electronic Engineering, JKUAT (P.O. Box 62000-00200 Nairobi; e-mail: emureu@jkuat.ac.ke ; Tel: +254724264675).*
P.K. Kihato, Department of Electrical and Electronic Engineering, JKUAT (email: pkihato@jkuat.ac.ke) and P.K.Langat, Department of Telecommunication Engineering, JKUAT (e-mail:kibetlp@jkuat.ac.ke)

Modulation Classification (AMC) as a means of performing spectrum sensing, to verify whether a given channel is in use by a primary user or not.

Automatic Modulation Classification (AMC) was first motivated by its application in military scenarios where electronic warfare, surveillance and threat analysis require the recognition of signal modulations, in order to identify adversary transmitting units, to prepare jamming signals, and to recover the intercepted signal. AMC has also been used in civilian applications like Link adaptation [8].

A lot of research has been done in this field of AMC and following are few of them. Thakur et. al., [9] documented an exhaustive survey, starting from very early methods to most promising recent techniques that are being applied to AMC problem. They concluded that feature based approach has higher potential against decision theoretic approaches. Mohammad et. al., [10] compared the use of modulation classification as means of spectrum sensing with other conventional methods. They concluded that in practice, developing reliable and fast spectrum sensing method for cognitive radio systems using modulation classification is still a great challenge, especially over multipath fading channel and in the presence of non-Gaussian impulsive noise, where the received signal experiences a very deep fade. Elrharras et. al., [11] combined energy detector and modulation classifier for spectrum sensing. Principal component analysis was used to extract signal features and neural network was used to make the decision. Their evaluation showed that the performance of detection is independent from modulation type, and also proved that dimensionality reduction does not influence the classification rate.

Zhu et. al., [8] analyzed various modulation classifiers that included Likelihood-based, Distribution Test-based and Machine learning-based. They discovered that the requirement for channel parameters varied among most classifiers. They found that the best classifier that was able to classify most digital modulations, while not needing much prior knowledge of the communication system, was the Expectation maximization-Maximum Likelihood (EM-ML) classifier. While being versatile and robust, the disadvantage of the EM-ML classifiers was their high computation complexity, as they required a high number of exponentiation and logarithms.

An ideal modulation classifier should be able to work with minimal or no prior knowledge of the communication system, have good performance in moderately low SNR and have low computation complexity. Amongst the classifiers studied above none fulfilled all of these requirements.

This study aimed at developing an Automatic Modulation Classifier for spectrum sensing, that tries to moderately fulfill all the three requirements of an ideal classifier. We proposed a classifier based on Deep Learning (DL) methods, which can automatically extract features. DL is a branch of machine learning and has achieved remarkable success because of its excellent classification ability. DL has been applied in many fields, such as image classification [12] and natural language processing [13]. Several typical DL networks, such as a Deep Belief Network(DBN) [13], and Convolutional Neural Network (CNN) [14], have been applied in AMC. Amongst the three DL architectures, the CNN has been selected in this study, for use in the implementation of the AMC, for several reasons. Firstly, the CNNs are the first truly successful deep learning architecture due to the successful training of the hierarchical layers. Secondly, the CNN topology leverages spatial relationships, so as to reduce the number of parameters in the network, and the performance is therefore improved using the standard backpropagation algorithms. Finally, the CNN model requires minimal pre-processing [15].

The remainder of the paper is organized as follows: Material and Methods are explained in Section II, followed by the Results and Discussion in Section III, and finally Conclusion and Recommendation in Section IV.

II. MATERIAL AND METHODS

In this study a laptop running Convolution Neural Network in MATLAB Release 2019 software was used, to carry out simulations of an Automatic Modulation Classifier in the context of spectrum sensing for cognitive radio systems.

Synthetic, channel-impaired waveforms were generated to train a CNN for modulation classification. The CNN was then tested with a set of test data for modulation classification of various modulation types under varying SNR values that ranged between -40dB to +40dB.

The CNN in this study was trained to recognize the eight digital and three analog modulation schemes shown in Table 1

Table 1 Modulation schemes

Digital modulation schemes	**Analog modulation schemes**
Binary phase shift keying (BPSK)	Broadcast FM (B-FM)
Quadrature phase shift keying (QPSK	Double sideband amplitude modulation (DSB-AM)
8-ary phase shift keying (8-PSK)	Single sideband amplitude modulation (SSB-AM)
16-ary quadrature amplitude modulation (16-QAM)	
64-ary quadrature amplitude modulation (64-QAM)	
4-ary pulse amplitude modulation (PAM4)	
Gaussian frequency shift keying (GFSK)	
Continuous phase frequency shift keying (CPFSK)	

The CNN that was used, consisted of six convolution layers and one fully connected layer as shown in Figure 1. Each convolution layer except the last was followed by a batch normalization layer, rectified linear unit (ReLU) activation layer, and max pooling layer. In the last convolution layer, the max pooling layer was replaced with an average pooling layer. The output layer had softmax activation. The Figure 1 show the structure of this Convolution Neural Network .on Classification CNN Convolution Neural Network .

The trained CNN took 1024 channel-impaired samples and predicted the modulation type of each frame.

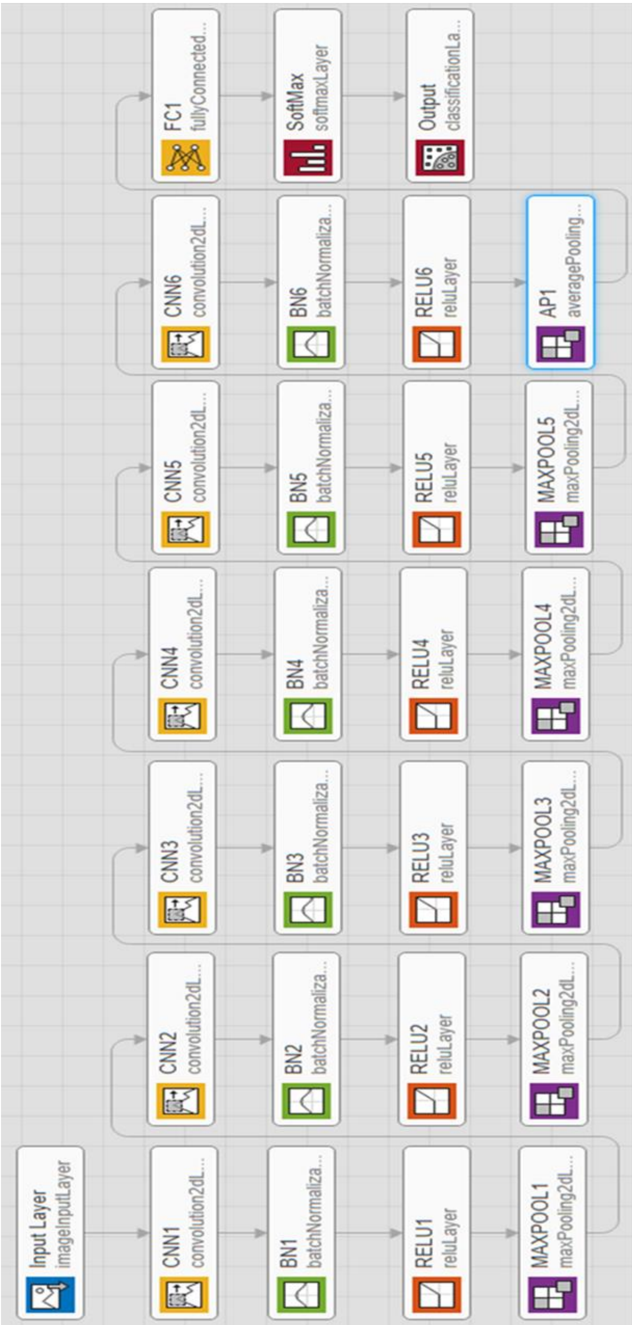

Figure 1 Convolution Neural Network Structure

Ten thousands frames for each modulation type were generated, where 80% was used for training, 10% was used for validation and 10% was used for testing. The training and validation frames were used during the network training phase. Final classification accuracy was obtained using test frames. Each frame was 1024 samples long and had a sample rate of 200 kHz. For digital modulation types, eight samples represented a symbol. The network made each decision based on single frames rather than on multiple consecutive frames (as in video). The center frequency of 900 MHz and 100 MHz for the digital and analog modulation types were assumed respectively.

Each frame was passed through a channel with Additive White Gaussian Noise (AWGN), Rician multipath fading, Clock offset, resulting in center frequency offset and sampling time drift as detailed below .

i. Added White Gaussian Noise (AWGN)

The channel added AWGN with SNR values that ranged between -40dB to +40 dB. The noise standard deviation, was calculated as

$$std = \sqrt{10.\hat{}\,(-SNR/10)} \text{……….1}$$

Where *std* is the noise standard deviation, SNR is the Signal to Noise Ratio and .^ is the Array exponentiation operator.

The channel was Implemented using comm.AWGNChannel MATLAB function.

ii. Rician Multipath

The channel passed the signals through a Rician multipath fading channel using the comm.RicianChannel System object. A delay profile of [0 1.8 3.4] samples with corresponding average path gains of [0 -2 -10] dB was assumed. The K-factor was set at 4 and the maximum Doppler shift at 4 Hz, which is equivalent to a walking speed at 900 MHz.

iii. Clock Offset

Clock offset occurs because of the inaccuracies of internal clock sources of transmitters and receivers. Clock offset causes the center frequency, which is used to down -convert the signal to baseband, and the digital-to-analog converter sampling rate to differ from the ideal values. The channel simulator used the clock offset factor C, expressed as

$$C = 1 + ?clock * 10^6$$

where ?clock is the clock offset.

For each frame, the channel generates a random ?clock value from a uniformly distributed set of values in the range [?max?clock max?clock], where max?clock is the maximum clock offset. Clock offset is measured in parts per million (ppm). For this study, we assumed a maximum clock offset of 5 ppm.

iv. Frequency Offset

Each frame was subjected to a frequency offset based on clock offset factor C and the center frequency. The comm.PhaseFrequencyOffset function was used to implement this component of the channel.

v. Sampling Rate Offset

Each frame was subjected to a sampling rate offset based on clock offset factor C. The interp1 MATLAB function was used to resample the frame at the new rate of $C*f_s$, where f_s, is the sample rate.

A loop was created that generated a channel-impaired frames for each modulation type and stored the frames with their corresponding labels in frameStore MATLAB function. A random number of samples from the beginning of each frame were removed to remove transients and to make sure that the frames have a random starting point with respect to the symbol boundaries.

III. RESULTS AND DISCUSSION

In order to determine the optimal number of epochs, the SNR was held constant at 30dB and ran simulations with number of epochs ranging from 1 to 16. For each run, the percentage overall classification accuracy of the eleven modulation types was recorded. Figure 2 is a plot of these results. As the plot in Figure 2 showed, the network converged in about twelve epochs to almost 90% accuracy. Increasing the number of epochs beyond twelve did not give rise to significant rise in the classification accuracy, but increased the simulation time substantially. Hence, for the simulations carried out, twelve epochs were used..

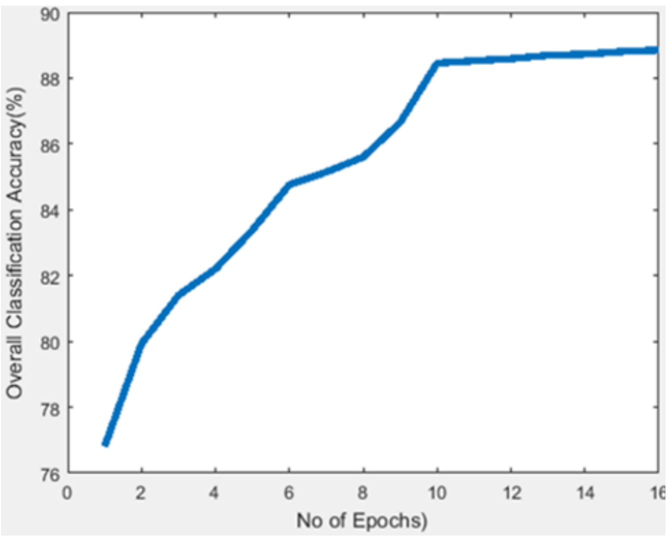

Figure 2 A plot of the modulation classification accuracy for different number of epochs.

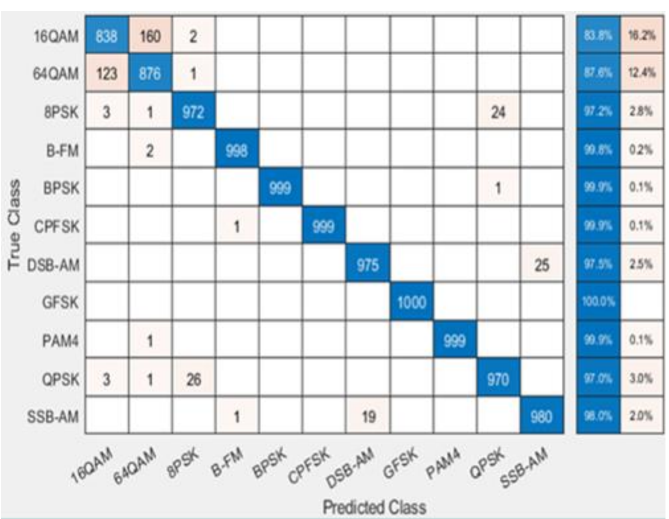

Figure 3 Confusion Matrix at SNR of 40dB.

The Figure 3 is the confusion matrix for an SNR of 40dB. As the matrix showed, the network confused 16-QAM and 64-QAM frames. This problem was expected since each frame carried only 128 symbols and 16-QAM is a subset of 64-QAM. The network also confused QPSK and 8-PSK frames, since the constellations of these modulation types look similar once phase-rotated due to the fading channel and frequency offset.

The Figure 4 is the plot of Individual Modulation Schemes percentage classification accuracy for different SNR values. As seen in Figure 3, more than half of the modulation schemes attained 100% classification accuracy with an SNR of as low as 15dB. The percentage of the classification accuracy is synonymous to the probability of detection. As a higher probability is desirable for a spectrum sensing scheme so is a higher percentage of the classification accuracy for the case when an AMC is being used for spectrum sensing. Most of the modulation schemes attained over 90% classification accuracy at SNR value of 20dB.

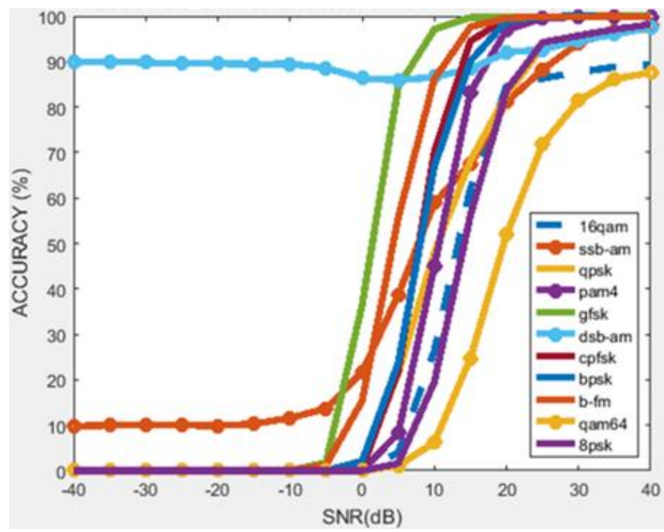

Figure 4 Individual Modulation Schemes Classification Accuracy for different SNR values.

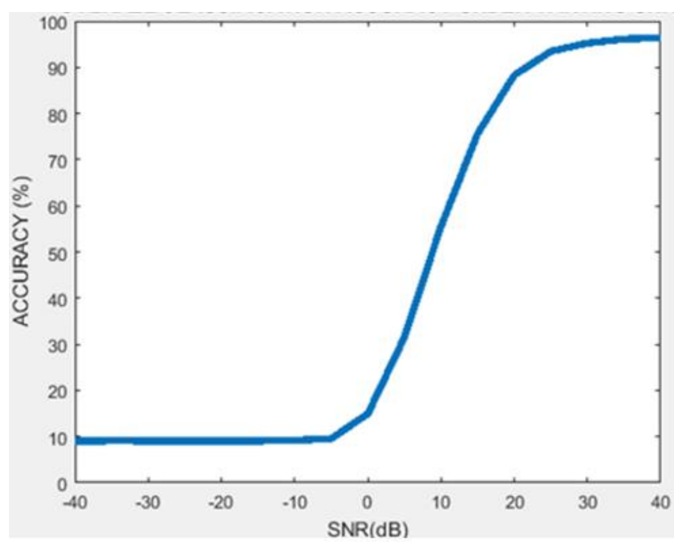

Figure 5 Overall Percentage Classification Accuracy for different SNR values.

Figure 5 showed the plot of the overall percentage classification accuracy for the eleven modulation schemes under different SNR values. As shown in the figure, the overall classification accuracy reached about 95% at about SNR of 30dB and then plateaued.

IV. CONCLUSION AND RECOMMENDATIONS

As the results have shown, the CNN based AMC could be used for spectrum sensing and give accurate results. The advantage of this method over other proposed methods, is that it could, with high accuracy, detect signals whose prior details is not available even under moderately low SNR values.
The results in this study were for signals that were synthetically generated through simulation. As a recommendation for future work, real time and over the air signals could be used instead.

ACKNOWLEDGEMENT

The authors would like to acknowledge the AFRICA-ai-JAPAN Project and the Jomo Kenyatta University of Agriculture and Technology for the research fund award.

REFERENCES

[1] Al-Hourani.A, Trajkovic.V,Chandrasekharan.S and S.Kandeepan.S (2015). Spectrum Occupancy Measurements for Different Urban Environments. European Conference on Networks and Communications (EuCNC), pp. 97-102
[2] Kurnaz C., Engiz B., and Albayrak Z. (2016). Measuring and Evaluating TV White Spaces in Samsun, Turkey. Journal of new Results in Science , No. 12, pp. 139 -148.
[3] Kiftaro F., El-Tarhuni M., and Assaleh K. (2017). UHF Spectrum Occupancy Measurements in Sharjah - UAE. IEEE-GCC Conference and Exhibition (GCCCE). 9 , 1-5
[4] Cardenas M., Diaz M., Pineda U., Arce A. and Stevens E. (2016). On spectrum occupancy measurements at 2.4 GHz ISM band for cognitive radio applications. International Conference on Electronics, Communications and Computers (CONIELECOMP). pp. 25-31
[5] Balina P., Garg K. and Rao S. (2014). Spectrum occupancy measurements and analysis in a rural area setting. International Conference on Parallel, Distributed and Grid Computing. pp. 412-416
[6] Popoola J.J, Ogunlana O.A, Ajie F.O, Olakunle O., Akiogbe O.A., Ani-Initi S.M. and Omotola S.K. (2016). Dynamic Spectrum Access: A New Paradigm of Converting Radio Spectrum Wastage to Wealth. International Journal of Engineering Technologies. 2, 3, 124-131
[7] Y¨ucek T. and Arslan H. (2009). A Survey of Spectrum Sensing Algorithms for Cognitive Radio Applications. IEEE Communications Surveys and Tutorials. 11,1, 116-130
[8] Zhu.Z and Nandi A.K (2015) Automatic Modulation Classification Principles, Algorithms and Applications. pp 1. John Wiley & Sons Ltd, UK.
[9] Thakur P.S. , Madan S. , Madan M. (2015), Trends in Automatic Modulation Classification for Advanced Data Communication Networks. International Journal of Advanced Research in Computer Engineering & Technology. 4 ,2, 496-507
[10] Mohammad R. B, Mohd Z.Y, Abdel-Haleem A., M. Naufal and Lamis K.(2017), Spectrum Sensing for Cognitive Radio Systems Using Modulation Classification: A Review. Applied Mathematics & Information Sciences. 2,3, 857-865
[11] Elrharras A. , Saadane R., Wahbi M. and Hamdoun A. (2014), 2Signal Detection and Automatic Modulation Classification Based Spectrum Sensing Using PCA-ANN with Real Word Signals. Applied Mathematical Sciences. 8,160 ,7959 - 7977
[12] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, A. Rabinovich, in Proceedings of the IEEE conference on computer vision and pattern recognition. Going deeper with convolutions, (2015), pp. 1–9.
[13] Y. Wu, M. Schuster, Z. Chen, Q. V. Le, M. Norouzi, W. Macherey, M. Krikun, Y. Cao, Q. Gao, K. Macherey, et al.. (2016) Google's neural machine translation system: bridging the gap between human and machine translation. (2016).
[14] A. Dai, H. Zhang, H. Sun, (2016). Automatic modulation classification using stacked sparse auto-encoders, IEEE 13th International Conference on Signal Processing (ICSP) pp. 248–252.
[15] T. J. O'Shea, J. Corgan, T. C. Clancy, (2016). Convolutional radio modulation recognition networks. International Conference on Engineering Applications of Neural Networks. (Springer, 2016), pp. 213–226.