International Journal of Mobile Network Design and Innovation

ISSN online: 1744-2850 - ISSN print: 1744-2869
https://www.inderscience.com/ijmndi

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DOI: 10.1504/IJMNDI.2023.10058172

Article History:

Received:	23 May 2023
Last revised:	02 June 2023
Accepted:	09 June 2023
Published online:	03 September 2023

Analysis of unsupervised primary-secondary user recognition using DTW and DFW in cognitive radio networks

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Abstract: Primary user (PU) and secondary users (SU) identification is critical to tiered spectrum sharing algorithms in cognitive radio (CR) networks. This paper focuses on a methodology to improve PU and SU identification using unsupervised classical learning methods. An experimental approach is studied using dynamic time warping (DTW) and dynamic frequency warping (DFW), which is DTW applied to the frequency domain. Principal component analysis (PCA) is used as a lightweight autoencoder. This work's focus is to minimise the need for extensive training data and class labelling for efficient cognitive node deployment. A variety of different modulations are explored including quadrature amplitude modulation (QAM), phase shift keying (PSK), pulse amplitude modulation (PAM), frequency shift keying (FSK), amplitude modulation (AM), and frequency modulation (FM).

Keywords: cognitive radio; DTW; dynamic time warping; DFW; dynamic frequency warping; machine learning; primary-secondary user detection.

Reference to this paper should be made as follows: Miller, S.G. and Kump, P.M. (2023) 'Analysis of unsupervised primary-secondary user recognition using DTW and DFW in cognitive radio networks', *Int. J. Mobile Network Design and Innovation*, Vol. 10, No. 4, pp.233–239.

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This paper is a revised and expanded version of a paper entitled 'Unsupervised primary-secondary user identification using DTW and DFW in dynamic wireless environments' presented at *Wireless Telecommunications Symposium 2023 (WTS 2023)*, Boston, MA, USA, April 2023.

1 Introduction

Cognitive radio (CR) seeks to solve many of the problems currently plaguing global wireless communications sectors. Wireless spectrum allocation is a finite resource that is currently strained as certain frequency bands are more lucrative than others, either through regulation or physical propagation properties. In 2021, over 54% of the world's internet traffic was conducted on mobile phones (BroadBand, 2022). Furthermore, more than half of the world's internet traffic is carried over WiFi (Yu et al., 2020). The demand for more wireless services and growth of mobile devices has further worsened the overpopulation of the already scarce spectrum. The demand for fast and reliable mobile service has led network operators to deploy more base stations and increase transmission power to meet service demands. In 2020, the United States Federal Communications Commission (FCC) unlicensed a 1.2 GHz bandwidth in US to help alleviate such traffic (FCC, 2020). However, given the rate of wireless traffic growth, a need for more efficient spectrum utilisation becomes apparent.

Cognitive radio plays an enormous role in the expansion of unlicensed bands and exploits its inherent ability to mitigate interference between devices. However, existing CR solutions have suffered tremendous drawbacks in mass adoption as that they are impractical to roll out incrementally and often require heavy deep learning algorithms with a great deal of training data (Alshawaqfeh et al., 2015). This work seeks to alleviate the need for a burdensome deep learning algorithm in favour of unsupervised classical learning methods. A subdomain of CR systems involves opportunistic spectrum access, which heavily relies on analysing the dynamic wireless spectrum. The core principles of opportunistic spectrum access rely on spectrum monitoring. While spectrum monitoring has been researched for decades, CR has been an achievable outcome only in the past decade or so.

Dynamic spectrum monitoring has been at the forefront of CR applications for many years. More specifically, Primary-Secondary user (PU-SU) identification is a critical principle that allows for decision making within CR networks that involve either licensed and unlicensed users or prioritised channels such as emergency service radios. Early approaches to CR and PU-SU identification involved spectrum sensing and algorithmic channel mapping (Plata and Reatiga, 2012; Wang et al., 2013) and is still an important part of CR spectrum access management (Sarala et al., 2020; Thanuja et al., 2020). The shift towards machine learning (ML) and artificial intelligence (AI)-based decision-making focuses on the outcomes of spectrum sensing including PU-SU detection (Janu and Kumar, 2022)

There are opportunities for adversaries to attempt to spoof or masquerade themselves as primary spectrum users. However, multi-faceted approaches using ML techniques have been studied to counteract primary user emulation (PUE; Muñoz et al., 2022). While this is an apparent issue, this paper focuses primarily on non-malicious SU detection.

While DTW has been used extensively in various fields for automated detection such as automatic handwritten signature verification (Parziale et al., 2019), irregular heartbeat detection (Cathelain et al., 2019), and speech recognition (Sun et al., 2014), it is comparatively under studied for cognitive radio applications. Teronpi et al. (2021) shows one of the few experiments on DTW for modulation recognition. However, this paper does not elaborate on the modulation classification mechanisms and does not explain the feature extraction methodology other than deeming it a "DTW based algorithm". Therefore, it is not a direct equivocation of results compared with those in this paper.

2 Methodology

A novel feature extraction methodology for unsupervised PU-SU detection is presented in this paper which uses dynamic time warping (DTW), dynamic frequency warping (DFW), and principal component analysis (PCA). DTW is a commonly used technique in speech signal processing (Permanasari et al., 2019). However, this work explores the combination of DTW, DFW, and PCA with respect to signal features such as modulation comparisons, spectral characteristics, and time-frequency occupation. The goal of this research is to determine whether DTW and DFW can successfully differentiate between a known primary user (PU) and unknown secondary user (SU) when used in conjunction with the unsupervised PCA algorithm. The constraints set forth were to minimise the a-priori information of the PU and SU signals. Furthermore, an unsupervised ML algorithm was utilised as there are a fundamentally undefinable number of classes of SU's. Therefore, this approach provides a deterministic identification of either a PU or a comprehensive outlier group of any other modulation to be defined as a SU. Lastly, the choice of DTW with PCA reconstruction was driven by the need for real-time PU-SU recognition. DTW, and DFW by analogous nature, has been shown to improve computation speed in hardware accelerated platforms (Wang et al., 2013). Furthermore, PCA reconstruction inherently reduces the dimensionality of the data and therefore was a logical first choice for part of the classification engine.

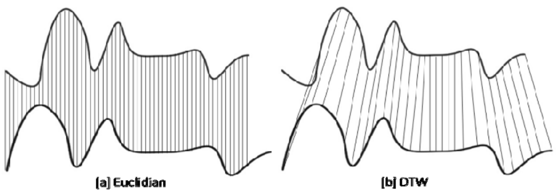
2.1 Dynamic time warping (DTW)

Dynamic time warping is at the most basic definition a metric to detect the similarities between two time-domain sequences. This is often calculated as the "distance" between the two signals under test. Cross correlation is a typical measure of distance in signal processing as it is computationally lightweight and provides a generally acceptable alignment in time. Inspiration to compare two signals' distance can be extracted from cross correlation by subtracting and taking the magnitude of each point. Equation (1) shows the generalised discrete form of Euclidean distance measurement for a dataset with N samples.

$$d(x, y) = \sum_{n=1}^{N} \left| x[n] - y[n] \right| \tag{1}$$

While Euclidean distance measurement, as in cross-correlation, is acceptable to use in signal similarity measurements, it only works well when the two signals are similar in Euclidean time. Euclidean distance is sensitive to slight temporal mismatches and is misleadingly large when otherwise identical signals are slightly time-dilated versions of each other. DTW provides an alternative to Euclidean distance measurements such as correlation as it finds the optimal match, the warp path between two signals. Figure 1 shows this comparison.

Figure 1 Euclidean (a) vs. DTW (b) distance visualisation



Source: Cross (2011)

A single value at point (*i, j*) in the DTW algorithm can be recursively formulated in equation (2)

$$dtw(i,j) = \left|x[i] - y[j]\right| + \min\begin{Bmatrix} dtw[i+1,\ j] \\ dtw[i+1, j+1] \\ dtw[i,\ j+1] \end{Bmatrix} \tag{2}$$

where *i* and *j* are indexes of each respective signal. It should be noted that this will form an $i \times j$ matrix which entails a computational complexity of $O(N^2)$. However, this work utilises a complexity-improved DTW algorithm, the FastDTW (Salvador and Chan, 2004). The FastDTW works on similar principles as the traditional DTW, but only calculates part of the $i \times j$ matrix. This is achieved by only calculating a local neighbourhood matrix around the warp path as defined by a tuning parameter, the radius. This in turn reduces the computational complexity to $O(N)$ for small radii.

2.2 Dynamic frequency warping (DFW)

Like DTW, DFW operates on complex frequency-domain sequences, measuring the distance between two Fourier transforms (FTs). DFW uses the same processing algorithm as shown in equation (2) with FTs of the input signals rather than the time domain signals. Similarly, all principles of the FastDTW apply to the frequency domain "FastDFW". If a DTW matrix of signal *x* and signal *y* is defined in equation (2), then a DFW of signal *x* and signal *y* can be defined as

$$dfw(i,j) = \left|X[i] - Y[j]\right| + \min\begin{Bmatrix} dfw[i+1,\ j] \\ dfw[i+1, j+1] \\ dfw[i,\ j+1] \end{Bmatrix} \tag{3}$$

where *X* and *Y* are FTs of *x* and *y* respectively.

This concept seeks to utilise the frequency domain information to formulate a feature matrix for input to a machine learning (ML) algorithm. This is performed by constructing a feature matrix such that the element at row i, column j, is DFW(*i*, *j*). The *i*th row is a vector of length *m* that provides the DFW measure of *X*[*i*] relative to each of the *m* FTs, including itself. This is known as the feature vector of the *i*th data point. This feature vector derived from the DFW is what is used within the unsupervised ML algorithm defined within this paper.

2.3 Principle component analysis (PCA)

PCA is a dimensionality reduction method that is beneficial in machine learning. Dimension reduction is useful for reducing computational effort, data visualisation, and guarding against overfitting – the tendency of ML algorithms to learn non-existent patterns in the data when provided too many features. Given an arbitrary dimensional set of features, PCA extracts new features called principal components (PCs) which are mutually orthogonal, linear combinations of the original features. The first PC captures the axis of maximum data variance, the second, the second most axis of maximum data variance, and so on.

PCA reconstruction is an extension of PCA that enables the algorithm to detect outliers, by examining the error of reconstructing a datapoint from its dimensionally reduced representation. PCA reconstruction was chosen as a preliminary means to detect outliers as it is a lightweight algorithm that is friendly to low-cost hardware implementations. Other outlier detection mechanisms can be tested in future work. Provided a set of *m* reconstruction errors *e*[*i*], *i* = 1, …, *m*, one may apply statistical techniques to select an appropriate threshold. The first quartile Q1 is defined as the error halfway between the lowest error and the median error. Similarly, the third quartile Q3 is the error halfway between the median and the largest error. Then, the interquartile range (IQR) may be calculated as IQR = Q3 – Q1. Finally, the threshold T may be set as T = Q3 + 1.5*IQR. This is a common threshold tuning method for PCA reconstruction (Yang and Rahardia, 2019).

3 Experiment formulation

This experiment was designed to explore the capability for PU-SU detection using DTW and DFW with PCA in an unsupervised algorithm. The focus is on baseline differentiation and autonomous detection of an unauthorised SU transmission or SU interfering signal. This paper is not meant to be an exhaustive set of scenario permutations, but rather a preliminary experiment to test the viability of DTW and DFW for these purposes. Research for malicious SU masquerading, SU localisation, operating frequency negotiation, system-level ML processes, and similar topics are not within the scope of this research. However, their implications are discussed in context throughout this paper. The chief outcome of this research is to utilise this unsupervised detection based primarily on PU-SU modulation differences and interference within a system. System-level ML scheduling and negotiation algorithms will be explored in future work.

The experimentation in this paper was performed using the HisarMod dataset (Tekbiy et al., 2019). The HisarMod dataset includes 26 modulation types from 5 different modulation families which are analogue, frequency shift keying (FSK), pulse amplitude modulation (PAM), phase shift keying (PSK), and quadrature amplitude modulation (QAM). In the dataset, there are 1500 signals, which have the length of 1024 I/Q samples, for each modulation type. There are 20 different SNR levels in between –20 dB and 18dB. The dataset encompasses 780000 different signals (Tekbiy et al., 2019). This dataset was initially designed to test blind modulation classification using deep learning techniques (Tekbıyık et al., 2020). Subsets of this dataset were taken for reduction of computational efforts. The selected data were chosen to represent either a targeted example scenario where PU-SU detection is needed, or a difficult to detect signal combination that was outlined in (Tekbıyık et al., 2020).

This algorithm is evaluated on data that are unseen by the algorithm during its learning phase, which in this case is parameter fitting of the PCA model. As per standard practice, the data were split into training and validation sets. These are described in each experiment within the Results section. Furthermore, it is necessary to utilise a separate validation set to calculate the threshold. For this reason, the HisarMod dataset was separated into three sets: training, validation, and testing. Each set is unique and mutually exclusive to the others. In order to preserve an unsupervised detection algorithm, no outlier data were included in the training data. Only outlier data were incorporated into the test dataset.

The feature vector for each experiment was created from this dataset by calculating the DTW/DFW distance of the test set from the training set. The relevant hyperparameters for this experiment are a DTW and DFW radius of one, with two principal components to observe data in a 2D space.

4 Results and analysis

Each experiment within this section uses DTW and DFW in combination with PCA reconstruction to calculate the F-1 score to quantify the evaluation metric. Accuracy, the number of total correct predictions divided by the total number of predictions made, is often misleading on its own (Sokolova et al., 2006). This is especially true in experiments with scarce outlier cases. The F-1 score, however, is the harmonic mean of precision and recall. Precision is defined as the number of correctly predicted outliers divided by the total number of predicted outliers. Recall is defined as the number of correctly predicted outliers divided by the total number of outliers. This provides results that are less dependent on the frequency of outlier occurrences.

4.1 8QAM PU with 32PSK SU

An experiment to demonstrate the outcomes of DTW, DFW and the combination of both features was constructed using 8QAM as the PU, and 32PSK as the SU. The signals were from the HisarMod dataset as outlined in the "Experiment Formulation" section. As previously mentioned, the goal was to design an experiment that showcases unsupervised learning using these features while minimising training data size and a priori information. For this reason, no signal metadata was used, and the sets are defined as follows:

1 *Training*: 60 PU signals
2 *Validation*: 20 PU signals (unique from training set)
3 *Testing*: 20 PU signals and 20 SU signals (unique from both training and validation sets).

This experiment was carried out for the select SNRs in the set [+18, +10, 0, –10, –20] dB. The experiment was run 100 different times, each time randomly generating mutually exclusive training, validation, and testing set.

In addition to the confusion matrix, the F-1 score was calculated for the aggregate of the 100 experiment runs. Figure 3 shows each SNR's experiment run where the data point is the mean of the runs, and the error bars extend to the best and worst case run in each SNR.

It is observed that the DTW with PCA performs adequately for the experiment. These results are comparable to those using trained deep learning models in relevant literature (Tekbiy et al., 2019; Abdel-Moneim et al., 2021) at different SNRs. However, the DFW alone did not produce meaningful results. Analysing the confusion matrixes in Figure 2, one can conclude that the DFW favoured identifying the SU as a PU signal. However, when used in a dimensional extension combined with the DTW, it is observed that there is not much improvement nor detriment to using the DTW with DFW in the outlined unsupervised PCA detector. However, all methodologies appear to begin to deteriorate as the SNR approaches 0 dB and lower. This is expected and is well documented in the literature.

4.2 64QAM PU with random (non-64QAM) SU

A similar experiment to the "8QAM PU with 32PSK SU" experiment was devised for a 64QAM PU and random, non-64QAM SU. This experiment was designed to showcase a more dynamic environment where the in-channel signal was of any unknown modulation from a wide SU class including 8PSK, 8PAM, 4FSK, AM-DSB, PM, and FM. Again, this goal outlines the need for unsupervised detection with minimal training data. For the same reasons, no signal metadata was used, and the sets are defined as follows:

1 *Training*: 60 PU signals
2 *Validation*: 20 PU signals (unique from training set)
3 *Testing*: 20 PU signals and 20 SU signals (unique from both training and validation sets).

Figure 4 shows the results from the 64QAM PU with random non-64QAM SU. This experiment showcased a promising result in that neither the DTW nor DFW alone performed well in correctly identifying a random SU.

However, a combination of both increased the performance of SU detection more than the sum of its parts. This result encourages further study of the usage of DTW plus DFW in PU-SU detection.

Figure 2 Confusion matrixes with 8QAM PU and 32PSK SU from 18 dB to –20 dB. True-positive defined as SU detection in this experiment (see online version for colours)

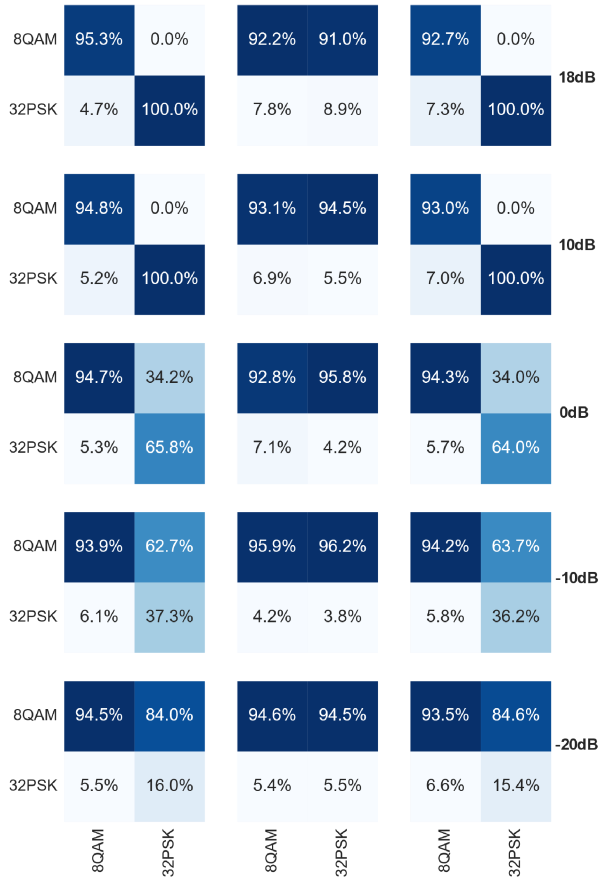
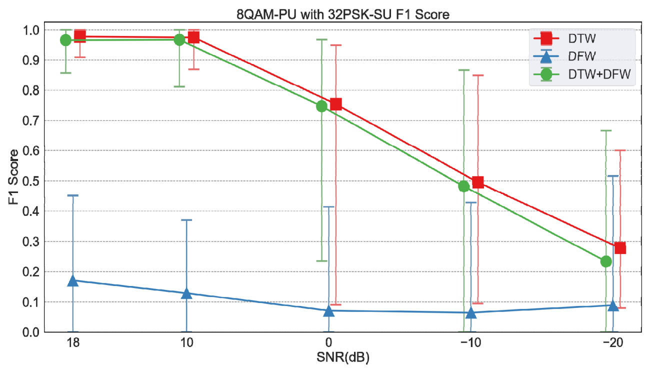


Figure 3 8QAM PU with 32PSK SU F1 score from 18 dB to –20 dB (see online version for colours)



Again, in addition to the confusion matrix, the F-1 score was calculated for the aggregate of the 100 experiment runs. Figure 5 shows each SNR's experiment run where the data point is the mean of the runs, and the error bars extend to the best and worst case run in each SNR.

Figure 4 Confusion matrixes with 64QAM PU and random (non-64QAM) SU from 18 dB to –20 dB. True-positive defined as PU detection (see online version for colours)

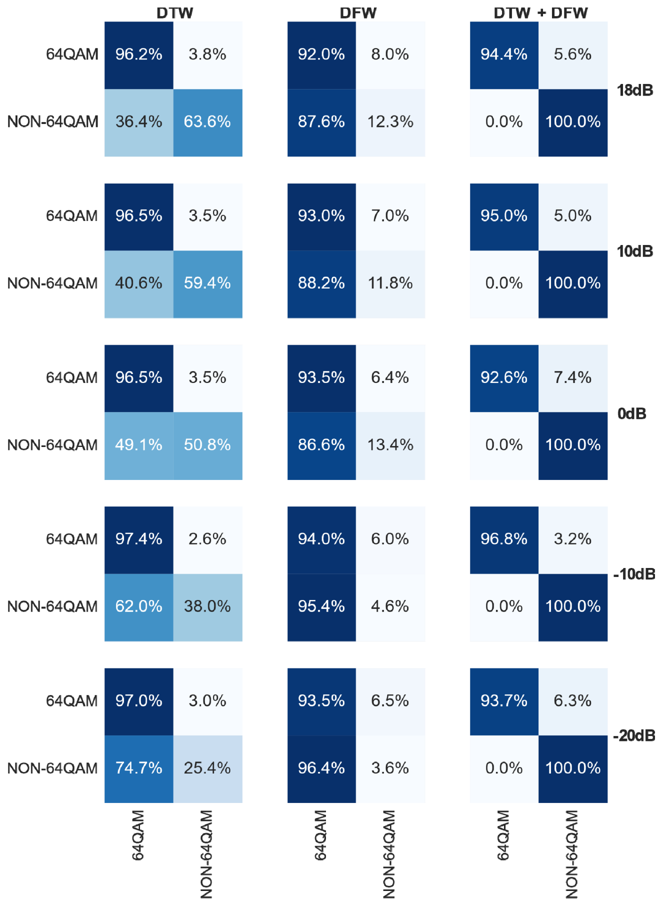
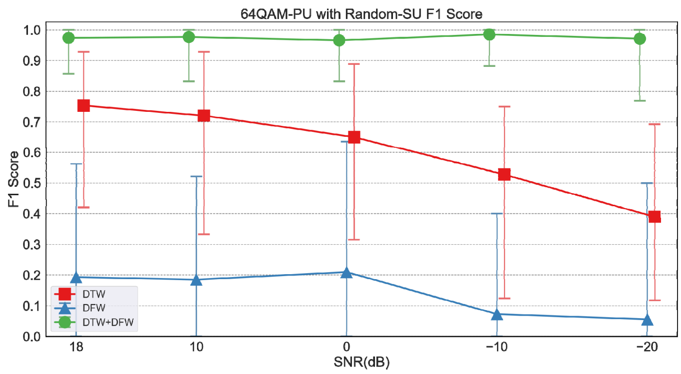


Figure 5 F1 score of 64QAM PU and random (non-64QAM) SU from 18 dB to –20 dB (see online version for colours)



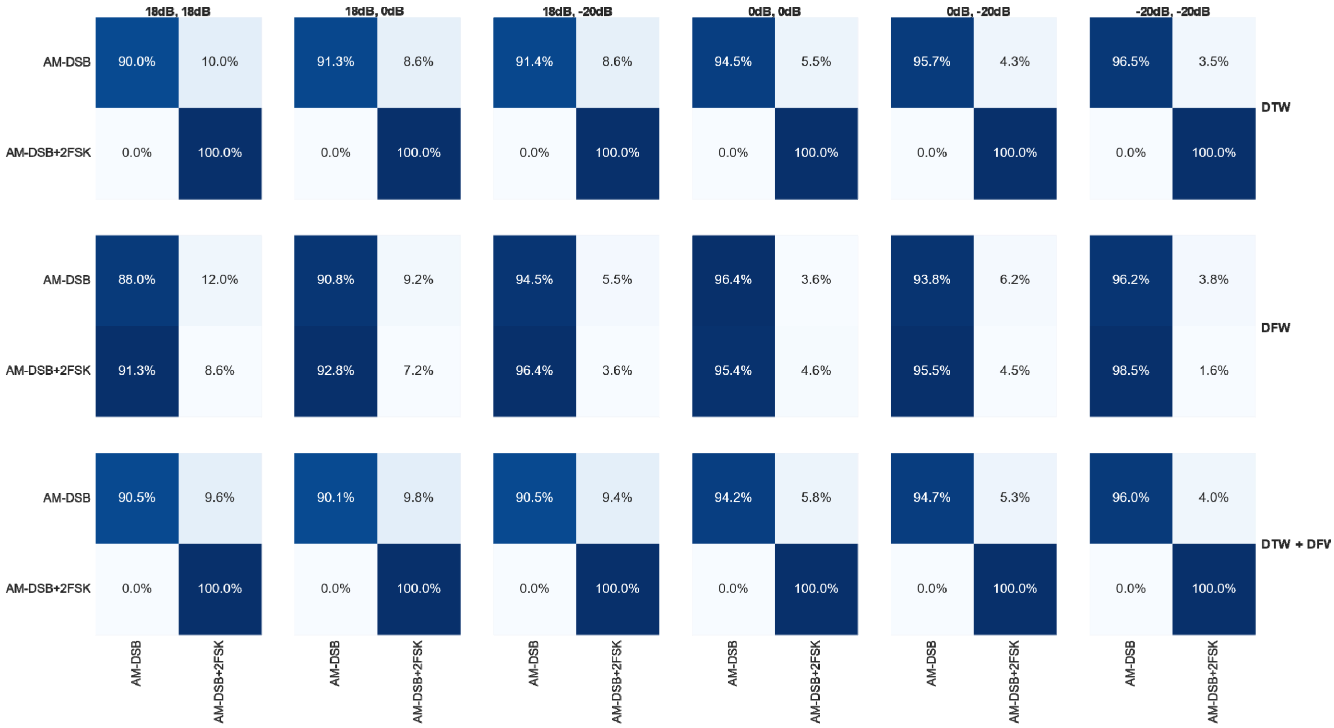
Similar to the 8QAM vs. 32PSK previously described, the DTW on its own favoured identification of the SU signal as a PU signal, especially at lower SNRs. However, the results from the DTW alone were not as accurate as the previous experiment. This is expected to be due to the more complex time envelope of higher order QAM signals than the previous experiment. This was the logical reasoning behind exploring the DFW. Similar to the previous experiment, the DFW did not perform well which was not expected given the visible difference in the frequency domain representation of the signals under test. Likewise, the DFW favoured the identification of SU as PU while used alone.

However, when combining the DTW and DFW in a multidimensional feature space, a drastic improvement to accuracy and F1 score were observed. This holds true even at lower SNRs. This can be seen most evident in Figure 5. The DTW with DFW feature set far outperformed the sum of their independent feature sets. The phenomenon of feature combination to a higher dimensional feature space is not unique and is often observed in both deep and classical learning alike. This result incentives further study as to which modulation schemes benefit the most from this feature combination. This will be discussed in the "Conclusions" section of this paper.

4.3 AM-DSB PU with AM-DSB+2FSK interferer SU

Lastly, an experiment was devised to emulate a common situation where a primary user is transmitting, and simultaneously experiences interference by an SU. This experiment used AM-DSB as the PU as up to this point all modulations tested were digital. The interferer used is 2FSK, a digital modulation. So, in turn, the classes are AM-DSB as PU, and AM-DSB+2FSK in the same channel as the SU. The SNRs of the signals were varied in a way as to keep the 2FSK SNR equal to or less than that of the AM-DSB to make detection more challenging and the experiment more realistic. Figure 6 shows the confusion matrixes of this experiment.

Figure 6 Confusion matrix of AM-DSB and AM-DSB+2FSK at various SNRs using DTW, DFW, and DTW + DFW (see online version for colours)



The results from this experiment show that the DTW is effectively able to detect when an interferer is present in the cases of the modulations explored. Surprisingly, the high SNR PU and low SNR SU performed well. This was unexpected as it was hypothesised that wide dynamic ranges, 38 dB in this case, did not reduce the detection capability of an interfering SU. This must be investigated on an application-to-application basis as there may be an acceptable level of interference for some systems, while others may be more stringent.

More consistently, the DFW did not provide any useful detection as a standalone feature. However, it should be noted that the DTW+DFW did not affect the PU-SU detection positively or negatively within any significant measurement. Therefore, there does not seem to be any risk in using both features together over just the DTW alone.

5 Conclusions

This work validated that through the usage of DTW and DFW plus PCA, one can effectively identify unknown and unlabelled SU signals from a known PU. Early results provided guidance that DTW is a valid feature extraction algorithm for unsupervised PU-SU detection. This capability was further exploited by taking a novel-to-application approach using the DTW algorithm's principles on the frequency domain to achieve DFW. The authors expected the DFW would help identify SU deviation of modulation type as it reflects the complex frequency domain which can be used in human-based modulation detection. Surprisingly, DFW showed little promise initially. However, experimentation combining a multi-dimensional feature set with both DTW and DFW features provided an example of how the amalgamation of these two features can differentiate PU-SU characteristics that are undetectable by either when used alone. This finding showcased a promising result in that neither the DTW nor DFW alone performed well in correctly identifying a random SU. However, a combination of both increased the performance of SU detection more than the sum of their parts. This finding reinforced the purpose of exploring the peripheral features using DTW plus DFW in future research. Furthermore, hyperparameter tuning will be a focus of future work to determine if these results can be improved. Wider DTW and DFW radii and higher numbers of PCs will be explored to determine the complexity tradeoffs of these hyperparameters with respect to performance.

References

Abdel-Moneim, M., El-Shafai, W., El-Salam, N., El-Rabaie, E-S. and Abd El-Samie, F. (2021) 'Survey of traditional and advanced automatic modulation classification techniques, challenges and some novel trends', *International Journal of Communication Systems*.

Alshawaqfeh, M., Wang, X., Ekti, A.R., Shakir, M.Z., Qaraqe, K. and Serpedin, E. (2015) 'A survey of machine learning algorithms and their applications in cognitive radio', *International Conference on Cognitive Radio Oriented Wireless Networks*.

BroadBand (2022) *Key Internet Statistics to Know in 2022 (Including Mobile)*, (Broadband Search) Retrieved January 2023, from https://www.broadbandsearch.net/blog/internet-statistics

Cathelain, G., Rivet, B., Achard, S., Bergounioux, J. and Jouen, F. (2019) 'Dynamic time warping for heartbeat detection in ballistocardiography', *Computing in Cardiology (CinC)*.

Cross, X. (2011) *Euclidean_vs_DTW.jpg*, 18 September, Retrieved January 2023, from https://commons.wikimedia.org/wiki/File:Euclidean_vs_DTW.jpg

FCC, F.C. (2020) *FCC Opens 6 GHz Band to Wi-Fi and Other Unlicensed Uses*, FCC News.

Janu, D.S. and Kumar, S. (2022) 'Machine learning for cooperative spectrum sensing and sharing: a survey', *Transactions on Emerging Telecommunications Technologies*, Vol. 33, No. 1.

Muñoz, E., Pedraza, L. and Hernández, C. (2022) 'Machine learning techniques based on primary user emulation detection in mobile cognitive radio networks', *Sensors*, Vol. 22, No. 13.

Parziale, A., Diaz, M., Ferrer, M. and Marcelli, A. (2019) 'SM-DTW: stability modulated dynamic time warping for signature verification', *Pattern Recognition Letters*, Vol. 121, pp.113–122.

Permanasari, Y., Harahap, E.H. and Ali, E.P. (2019) 'Speech recognition using dynamic time warping (DTW)', *Journal of Physics: Conference Series*, Vol. 1366, No. 1, p.012091.

Plata, D.M. and Reatiga, A.G. (2012) 'Evaluation of energy detection for spectrum sensing based on the dynamic selection of detection-threshold', *Procedia Engineering*, pp.135–143.

Salvador, S. and Chan, P. (2004) 'FastDTW: toward accurate dynamic time warping in linear time and space', *KDD Workshop on Mining Temporal and Sequential Data*, Seattle.

Sarala, B., Devi, S.R. and Sheela, J.J. (2020) 'Spectrum energy detection in cognitive radio networks based on a novel adaptive threshold energy detection method', *Computer Communications*, Vol. 152, pp.1–7.

Sokolova, M., Japkowicz, N. and Szpakowicz, S. (2006) 'Beyond accuracy, F-score and ROC: a family of discriminant measures for performance evaluation', *Australasian Joint Conference on Artificial Intelligence*.

Sun, X., Miyanaga, Y. and Sai, B. (2014) 'Dynamic time warping for speech recognition with training part to reduce the computation', *Journal of Signal Processing*, Vol. 18, No. 2, pp.89–96.

Tekbiy, K., k, C.K. and Gorcin, A. (2019) *HisarMod: A New Challenging Modulated Signals Dataset*, IEEE Dataport.

Tekbıyık, K., Ekti, A. R., Görçin, A., Kurt, G.K. and Keçeci, C. (2020) 'Robust and fast automatic modulation classification with CNN under multipath fading channels', *2020 IEEE 91st Vehicular Technology Conference (VTC2020-Spring)*, Antwerp.

Teronpi, K., Sarma, K.K., Misra, A. and Bhuyan, M. (2021) 'DTW based modulation detection-verification using software defined radio', *WSEAS Transactions on Communications*, Vol. 20, pp.133–138.

Thanuja, T., Daman, K.A. and Patil, A.S. (2020) 'Optimized spectrum sensing techniques for enhanced throughput in cognitive radio network', *2020 International Conference on Emerging Smart Computing and Informatics (ESCI)*, Pune.

Wang, N., Gao, Y. and Zhang, X. (2013) 'Adaptive spectrum sensing algorithm under different primary user utilizations', *IEEE Communications Letters*, Vol. 17, No. 9, pp.1838–1841.

Wang, Z., Huang, S. *et al.* (2013) 'Accelerating subsequence similarity search based on dynamic time warping distance with FPGA', *ACM/SIGDA International Symposium on Field Programmable Gate Arrays*.

Yang, J. and Rahardia, S. (2019) 'Outlier detection: how to threshold outlier scores', *International Conferences on Artificial Intelligence, Information Processing and Cloud Computing*.

Yu, L., Luo, B., Ma, J., Zhou, Z. and Liu, Q. (2020) 'You are what you broadcast: identification of mobile and IoT devices from (Public) WiFi', *29th USENIX Security Symposium*, Boston.