MACHINE LEARNING CLASSIFICATION OF FREQUENCY-HOPPING SPREAD SPECTRUM SIGNALS IN A MULTI-SIGNAL ENVIRONMENT

MUHAMMAD TURYALAI KHAN

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DEDICATION

This thesis is dedicated to my beloved family, friends, and all those who have contributed in this research.

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ABSTRACT

Frequency-hopping spread spectrum (FHSS) spreads the signal over a wide bandwidth, where the carrier frequencies change rapidly according to a pseudorandom number making signal classification difficult. Classification becomes more complex with the presence of additive white Gaussian noise (AWGN) and interference due to background signals. In this research, a hybrid convolutional neural network (HCNN) system with the fusion of handcrafted and deep features is proposed to classify FHSS signals in the presence of AWGN and the background signal. The CNN is used as a deep feature extractor by transforming the intermediate frequency (IF) signal to the time-frequency representation (TFR) and used as a two-dimensional (2D) input image, whereas the handcrafted features of the FHSS signal such as hop frequency and hop duration are estimated from the TFR. A proper network structure of the three-layer fully connected network (TLFCN) is determined and used as a classifier. The TLFCN is a machine learning algorithm that requires training with a proper dataset to classify the various types of FHSS signals. Ideally, the dataset size must be sufficiently large as well as balanced to optimize the classification performance. A pseudorandom sequence of hopping frequencies observed from an FHSS signal represents one observation of all the possible hopping sequences of the signal. Therefore, an observation calculating technique is developed that can derive the total number of possible hopping sequences of an FHSS signal by using the frequencies to determine the observations in the dataset. The majority of the machine learning algorithms assume that the training set is evenly distributed among classes. However, in many real-world applications, the number of observations among classes is often imbalanced, which reduces the classification performance of the algorithm. The number of observations of an FHSS signal depends on the number of hop frequencies. Therefore, a given set of FHSS signals with a varying number of hop frequencies among the FHSS signals results in an uneven number of observations, thereby building an imbalanced dataset. Thus, resampling and data augmentation methods such as synthetic minority oversampling technique (SMOTE) and random erasing (RE) are performed to balance the dataset for the increased learning and decision-making capacity of a machine learning algorithm. Monte Carlo simulation is performed to verify the classification performance of the linear discriminant (LD), TLFCN, CNN, and HCNN for various signal-to-noise ratio (SNR) levels. Based on the SNR range at 90% probability of correct classification (PCC) in the presence of AWGN and the background signal, the LD performed worst from 1 to 15 dB among all the methods, whereas the HCNN performed best from -1.58 to -0.66 dB. Moreover, the HCNN with the balanced dataset performed better by 0.14 to 1.06 dB of SNR than with the imbalanced dataset. Therefore, the HCNN system improved the classification performance and performed better than conventional machine learning-based algorithms.

ABSTRAK

Spektrum penyebaran frekuensi-lompat (FHSS) menyebarkan isyarat ke atas lebar jalur yang luas, di mana frekuensi pembawa berubah dengan cepat mengikut nombor pseudorandom yang menyukarkan klasifikasi isyarat. Pengelasan menjadi lebih kompleks dengan kehadiran hingar Gaussian putih tambahan (AWGN) dan gangguan akibat isyarat latar belakang. Dalam penyelidikan ini, sistem rangkaian neural perlingkaran hibrid (HCNN) dengan gabungan ciri buatan tangan dan mendalam dicadangkan untuk mengklasifikasikan isyarat FHSS dengan kehadiran AWGN dan isyarat latar belakang. CNN digunakan sebagai pengekstrak ciri dalam dengan mengubah isyarat frekuensi perantaraan (IF) kepada perwakilan frekuensi masa (TFR) dan digunakan sebagai imej input dua dimensi (2D), manakala ciri buatan tangan isyarat FHSS seperti kekerapan lompat dan tempoh lompat dianggarkan daripada TFR. Struktur rangkaian yang betul bagi rangkaian bersambung sepenuhnya tiga lapisan (TLFCN) ditentukan dan digunakan sebagai pengelas. TLFCN ialah algoritma pembelajaran mesin yang memerlukan latihan dengan set data yang betul untuk mengklasifikasikan pelbagai jenis isyarat FHSS. Sebaik-baiknya, saiz set data mestilah cukup besar serta seimbang untuk mengoptimumkan prestasi klasifikasi. Urutan pseudorandom frekuensi lompat yang diperhatikan daripada isyarat FHSS mewakili satu pemerhatian bagi semua kemungkinan jujukan lompat isyarat. Oleh itu, teknik pengiraan pemerhatian dibangunkan yang boleh memperoleh jumlah jujukan lompat yang mungkin bagi isyarat FHSS dengan menggunakan frekuensi untuk menentukan pemerhatian dalam set data. Kebanyakan algoritma pembelajaran mesin mengandaikan bahawa set latihan diagihkan sama rata antara kelas. Majoriti algoritma pembelajaran mesin menganggap bahawa set latihan diagihkan sama rata di antara kelas. Walau bagaimanapun, dalam banyak aplikasi dunia sebenar, bilangan pemerhatian antara kelas sering tidak seimbang, yang mengurangkan prestasi pengelasan algoritma. Bilangan cerapan isyarat FHSS bergantung pada bilangan frekuensi lompat. Oleh itu, set isyarat FHSS yang diberikan dengan bilangan frekuensi lompat yang berbeza-beza antara isyarat FHSS menghasilkan bilangan pemerhatian yang tidak sekata, dengan itu membina set data yang tidak seimbang. Oleh itu, kaedah pensampelan semula dan penambahan data seperti teknik pensampelan minoriti sintetik (SMOTE) dan pemadaman rawak (RE) dilakukan untuk mengimbangi set data bagi peningkatan kapasiti pembelajaran dan membuat keputusan bagi algoritma pembelajaran mesin. Simulasi Monte Carlo dilakukan untuk mengesahkan prestasi pengelasan diskriminasi linear (LD), TLFCN, CNN dan HCNN untuk pelbagai peringkat nisbah isyarat-ke-hingar (SNR). Berdasarkan julat SNR pada 90% kebarangkalian pengelasan betul (PCC) dengan kehadiran AWGN dan isyarat latar belakang, LD menunjukkan prestasi paling teruk dari 1 hingga 15 dB antara semua kaedah, manakala HCNN menunjukkan prestasi terbaik dari -1.58 hingga -0.66 dB. Selain itu, HCNN dengan set data seimbang menunjukkan prestasi yang lebih baik sebanyak 0.14 hingga 1.06 dB SNR berbanding set data tidak seimbang. Oleh itu, sistem HCNN meningkatkan prestasi klasifikasi dan berprestasi lebih baik daripada algoritma berasaskan pembelajaran mesin konvensional.

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LIST OF ABBREVIATIONS

AWGN	-	Additive White Gaussian Noise
ASK	-	Amplitude Shift Keying
ANN	-	Artificial Neural Network
BPSK	-	Binary Phase Shift Keying
CNN	-	Convolutional Neural Network
CE	-	Cross-Entropy
CV	-	Cross-Validation
EA	-	Electronic Attack
ES	-	Electronic Support
FCC	-	Federal Communications Commission
FCNN	-	Fully-Connected Neural Network
FHSS	-	Frequency-Hopping Spread Spectrum
FSK	-	Frequency Shift Keying
HCNN	-	Hybrid Convolutional Neural Network
ID	-	Imbalanced Data
ISM	-	Industrial, Scientific, and Medical
IEEE	-	Institute of Electrical and Electronics Engineers
IF	-	Intermediate Frequency
LD	-	Linear Discriminant
MWMOTE	-	Majority Weighted Minority Oversampling Technique
NN	-	Neural Network
OFDM	-	Orthogonal Frequency-Division Multiplexing
1D	-	One-Dimensional
PSK	-	Phase Shift Keying
PCC	-	Probability of Correct Classification
PN	-	Pseudo-Noise
QTFD	-	Quadratic Time-Frequency Distribution
QPSK	-	Quadrature Phase Shift Keying
RF	-	Radio Frequency
RE	-	Random Erasing

ROS	-	Random Oversampling
RUS	-	Random Undersampling
ResNet	-	Residual Network
STFT	-	Short Time Fourier Transform
SNR	-	Signal-to-Noise Ratio
SVM	-	Support Vector Machine
SMOTE	-	Synthetic Minority Oversampling Technique
TLFCN	-	Three-Layer Fully Connected Network
TF	-	Time-Frequency
TFD	-	Time-Frequency Distribution
TFR	-	Time-Frequency Representation
2D	-	Two-Dimensional
WVD	-	Wigner-Ville Distribution

LIST OF SYMBOLS

$a(t)$	-	Information bearing signal
$f_c(t)$	-	Time-varying channel frequency
T	-	Signal duration
f_c	-	Constant channel frequency
f_k	-	Subcarrier frequency
A	-	Signal amplitude
N	-	Signal length
N_w	-	Window size
$w(n)$	-	Window function
$x(n)$	-	Discrete signal
$S_x(n,k)$	-	Time-frequency representation
$P_x(k)$	-	Power spectrum
$P_T(k)$	-	Threshold power across spectrum
P_{T_def}	-	Default noise threshold power
$P_B(k)$	-	Maximum power of background signal
f_p	-	Peak frequency
f_{BW}	-	Signal bandwidth
f_{upp}	-	Upper frequency
f_{low}	-	Lower frequency
$P_i(n)$	-	Instantaneous power
P_{hs}	-	Possible hopping sequences
n	-	Number of hop frequencies of an FHSS signal
s	-	Required sample size
X^2	-	The chi-square value for 1 degree of freedom at desired confidence level, which is 3.841
N_p	-	Population size
P_p	-	Population proportion (assumed to be 0.5 as this will provide maximum sample size)
d	-	Degree of accuracy expressed as a proportion, which is 0.05

$\mathbf{w}$	-	Weight vector
$\mathbf{x}$	-	Feature vector
w_0	-	Bias
$d(\mathbf{x}, \mathbf{y})$	-	The Euclidean distance
l	-	Number of elements in a vector
S	-	Synthetic observation
M_1	-	Randomly selected minority observation
M_2	-	Nearest neighbour
r	-	Uniformly distributed random number between 0 and 1
P	-	Precision
R	-	Recall
$F1$	-	$F1$-score
$F1_{avg}$	-	Average $F1$-score
AP	-	Average precision
mAP	-	Mean average precision

CHAPTER 1

INTRODUCTION

1.1 Background

Multi-signal environment contains different types of wireless technologies which share a common frequency band [1]. An example would be Bluetooth, Wi-Fi, and Zigbee sharing the 2.4 GHz frequency [2]. Depending on the wireless technology, the signals may have either a fixed or variable carrier frequency. Most important there should not be any overlap of carrier frequency between the various wireless technologies which could cause interference between the various users. For example, two different Wi-Fi users can interfere with each other. Thus, a spectrum monitoring system can be utilized to manage the use of carrier frequency between the various wireless technologies as well as to detect unknown or unauthorized signal sources [3].

Among the functions that a spectrum monitoring system performs includes the detection, estimation of modulation parameters, classification, and geolocation of signals of interest over a wide area in a range of complex spectrum environments [3]. Its features are application-dependent and performed by regulatory bodies for compliance to the allocated spectrum. The system should be able to continuously sense weak signals over a large bandwidth, allocates definite spectrum to users, and identifies unlicensed spectrum users and sources of interference [4, 5]. For the military, spectrum monitoring is known as electronic support (ES) that estimates the parameters of signals such as communication and radar from the radio frequency (RF) emission by non-cooperative intercept [6, 7]. The information can be used for electronic attack (EA) by targeting the sources and locations of radio emissions. All electronic countermeasures such as electromagnetic jamming and deception approaches are covered by EA. The ES system can analyze complex communication signals, radar signals and low probability of intercept (LPI) signals such as frequency hopping spread spectrum (FHSS) signals which are difficult to intercept and process [8, 9]. The aim of the ES system is to intercept the emission from radar and communication of the target system. It is also used in EA to identify the frequency used by the adversary and take necessary actions to jam the emitter.

FHSS is a spread spectrum technique where the frequency is switched randomly according to a pattern known to both communicating parties for the synchronized communication [1]. The pseudo-noise (PN) sequence is used to generate the random number to change the carrier frequency [10, 11]. FHSS is used in both military and civilian applications. Examples of the FHSS applications are drones [12], military radios like single channel ground and airborne radio system (SINCGARS) [13], and low-power applications such as Bluetooth and LoRa [14]. Drones for example use FHSS to avoid interference from other drones by using a hopping sequence that is pre-shared between a sender and a receiver and each drone has a unique identification number programmed by its manufacturer. Thus, multiple drones can be flown in the same area without interfering with each other. FHSS is employed by the military to avoid eavesdropping and jamming by initializing the radio with an accurate time of day (TOD), a word of the day (WOD), and a network (NET) number [15]. Furthermore, the signal emitted from an FHSS transmitter is spread in frequency over a large bandwidth to reduce interception by an adversary. The use of FHSS systems is allowed by the Federal Communications Commission (FCC) in unlicensed frequency bands such as 2.4 GHz and 5.8 GHz where a user does not need any licence to use the spectrum. This can lead to FHSS abuse, for example, the use of drones in an abusive manner could be a rogue device [16]. Examples of recent incidents related to drone abuse: an oilfield in Abqaiq, Saudi Arabia was attacked by drones on September 14, 2019, which caused a 50% cut in oil production [17] and a bag of drugs was tried to be smuggled with a drone that was spotted by the police at Kranji, Singapore, on June 17, 2020 [18]. The military needs to detect the frequency of an FHSS signal used by its adversary through ES and use the information to apply EA. To prevent the misuse of FHSS based wireless technologies, a system is required to monitor, identify, and classify the signals.

1.2 Problem Statement

FHSS spreads the signal over a wide bandwidth, where the carrier frequencies change rapidly according to a pseudorandom number making signal classification difficult [19, 20]. Furthermore, interference occurs between the FHSS-based wireless technology (Bluetooth and drones) and fixed-frequency wireless technology (Wi-Fi) due to the sharing of a common frequency band such as 2.4 GHz [12] [21]. Therefore, classification becomes more complex with the presence of additive white Gaussian noise (AWGN) and interference due to background signals.

A machine learning algorithm requires training with a proper dataset to classify the various types of FHSS signals [22]. Ideally, a dataset size must be sufficiently large as well as balanced to optimize the classification performance. A pseudorandom sequence of hopping frequencies observed from an FHSS signal represents one observation of all the possible hopping sequences of the signal. Therefore, a technique is required that can derive the total number of possible hopping sequences of an FHSS signal to determine the observations in the dataset.

Most machine learning algorithms assume that the training set is evenly distributed among classes [23]. However, in many real-world applications, the number of observations among classes is often imbalanced, which reduces the classification accuracy of a machine learning algorithm [24-26]. The number of observations of an FHSS signal depends on the number of hop frequencies. Therefore, a given set of FHSS signals with varying hop frequencies among the FHSS signals results in unequal observations, thereby building an imbalanced dataset. Thus, a method is required to balance the dataset for increased learning and decision-making capacity of a machine learning algorithm.

Deep learning is the subset of machine learning, where a prime issue for signal classification is to pre-process a signal and represent it in an appropriate format [27-29]. Furthermore, a set of accurately conditioned images is required in the dataset to train an image classification network. Therefore, a given set of FHSS signals needs to be transformed into precise conditioned images to train a deep learning algorithm.

The majority of the existing algorithms lack the complementarities among different features as well as the significance of features fusion [30, 31]. For example, traditional machine learning and deep learning algorithms use either handcrafted or image features for training. The fusion of the handcrafted features with convolutional neural network (CNN)-based image features can be an effective method to form more discriminating features for further improving the classification performance, where these two types of features are complementary.

1.3 Research Objectives

The following are the objectives of this research:

1. To propose a technique that can derive the total number of possible hopping sequences of an FHSS signal by using the frequencies to determine the observations in the dataset.

2. To develop a system of pattern recognition by using the appropriate parameters of the FHSS signals such as hop frequency and hop duration for the classification in the presence of AWGN and background signal.

3. To perform the resampling techniques for balancing the dataset of the FHSS signals by making synthetic observations from the minority class observations for the effective training of a machine learning algorithm.

4. To develop a hybrid system by fusing CNN based features with handcrafted features such as hop frequency and hop duration, which will be used as input to the three-layer fully connected network (TLFCN) for FHSS signals classification in the presence of AWGN and background signal.

5. To evaluate the classification performance by using Monte Carlo simulation, box plots, mean average precision, and $F1$-score.

1.4 Scope of Work

1. The signal of interest is the FHSS signal that is the type of spread spectrum signal.

2. In this research, the signal at radio frequency (RF) is down-converted to the IF signal with the frequency range of 0 to 100 MHz.

3. The spectrogram of the FHSS signals is produced by the squared magnitude of the short-time Fourier transform (STFT) to obtain the time-frequency representation (TFR).

4. The parameters of the FHSS signal such as hop frequency and hop duration are estimated from the TFR of the FHSS signals.

5. The estimated parameters of the FHSS signal such as hop frequency and hop duration are provided as input to the TLFCN.

6. For deep learning, the size of the TFR of the FHSS signals is down-sampled to 224×224×3 and used a two-dimensional (2D) input image to the CNN.

7. For hybrid system, the residual network (ResNet) with 101 convolutional layers is used as deep feature extractor, whereas handcrafted features involve the estimation of hop frequency and hop duration from the TFR. These features are fused and used as input to the TLFCN.

8. The fixed-frequency signal such as OFDM (Wi-Fi) is used as the background signal while interference is modelled as AWGN.

9. The research is focused on the classification of FHSS signals in the presence of AWGN and the background signal (Wi-Fi signal). The signal direction of arrival is beyond the scope of this work.

10. The implementation of this research is based on MATLAB simulation. This work can be used in real-applications that is beyond the scope of this work.

1.5 Research Flow

Following are the steps for the flow of this research:

i. **Literature review:** It includes vast accessible literature that is arranged in two portions. Basic concepts are studied which comprises spectrum monitoring, TF analysis, and machine learning techniques. In second portion, related techniques are reviewed according to the problem statements and research objectives. It contains analysis and parameter estimation of FHSS signals, sample size calculation, machine learning signal classification, and resampling and data augmentation techniques to balance the dataset.

ii. **Methodology:** The developed approach is based on the studied literature to resolve the research problems. Methodology for this research is the following:

   a. Time-frequency analysis.

   b. Parameter estimation and deep features extraction.

   c. Development of dataset composition.

   d. Development of resampling techniques to balance the dataset.

   e. Development of machine learning techniques to classify FHSS signals.

iii. **Experimental work:** Experimental work is conducted as follows:

   a. The spectrogram of the FHSS signals is produced by the squared magnitude of the short time Fourier transform (STFT) to obtain the TFR.

   b. Parameters of the FHSS signals such as hop frequency and hop duration are estimated from the TFR, whereas the CNN is used for deep features extraction.

   c. Determining the number of observations to compose the dataset for the training and testing of TLFCN, CNN, and HCNN.

d. Handling the imbalanced dataset by making synthetic, duplicate, or augmented observations from the minority class observations.

e. Classification of the FHSS signals is computed by the linear discriminant (LD), TLFCN, CNN, and hybrid CNN (HCNN).

iv. **Analysis and discussion:** Results achieved in the experimental work are discussed and the findings concluded are based on their analysis.

1.6 Thesis Organization

This thesis is organized into five chapters and the contents of each chapter are as follows: Chapter 1 begins with the research background by explaining a multi-signal environment, spectrum monitoring, and characteristics and applications of FHSS signals. It is followed by the problem statement that includes FHSS signals classification, dataset derivation, imbalanced dataset, pre-processing and representation of the signal, and deficiency of existing algorithms. Thereafter, the objectives of the work are set according to the problem statement to solve them. Finally, the scope of the work followed by the research flow is described.

The literature review related to this study is presented in Chapter 2 which comprises spectrum monitoring, TF analysis, parameter estimation, machine learning and deep learning, and resampling and data augmentation techniques. All these research areas are comprehensively reviewed and summarized in Tabular form.

Chapter 3 describes the methodology of the research flow with graphical representations and mathematical equations. It includes the signal model and its parameters, time-frequency distribution, parameter estimation, the composition of the dataset, imbalanced dataset handling, and machine learning signal classification. Experiment flows including explanations are incorporated at the end of Chapter 3.

Results are shown and discussed in Chapter 4 which includes the time-frequency representation of the FHSS with background signal, the plots of classification performance, and cross-entropy error. Moreover, the classification performance is further explained by using the confusion matrix, box plots, mean average precision, $F1$-score, and significance analysis.

In Chapter 5, the conclusions are made according to the research objectives. It is followed by the contributions of work, where the contributions are described in paragraph form and then summarized in points. Finally, future work recommendations are suggested at the end of the chapter.

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