HYBRID FEATURE SELECTION TECHNIQUE FOR CLASSIFICATION OF HUMAN ACTIVITY RECOGNITION

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DEDICATION

This thesis is lovingly dedicated to my late father, who always encouraged me to learn and seek knowledge throughout my life. *Alfatihah*. This thesis also dedicated to my mother, who has shown me so much love and support. Additionally, this thesis is a dedication to my perseverance and refusal to give up.

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ABSTRACT

Through the advancement of wearable sensors, wireless communication, and machine learning techniques, Assistive Technologies (AT) which endorse autonomous, active, and healthy lifestyles are emerging in recent years. Among these advances, Human Activity Recognition (HAR) is one of the most innovative means to support or monitor older people in their daily lives. Extensive research in the field of HAR is also essential for the enhancement of the quality of a person's health. However, misclassifications such as intra-class variation and inter-class overlap in similar activities degrade classification accuracy. To improve the recognition of daily human activities, handcrafted features of time-domain and frequency-domain are combined. However, several extracted features may not be significant in describing the activities. Therefore, this research aims to propose a hybrid feature selection technique for optimal human activities recognition. The methodology proposed for this research is the Ensemble Filter (Relief-F and mRMR) to select the most relevant and less redundant features. Although a filter feature ranking approach is commonly used in related studies, most works fail to consider the threshold limit to exclude unnecessary and redundant features. The hybrid Binary Harmony Search-Artificial Bee Colony (BHS-ABC) algorithm further evaluated the quality of the selected features in this research. Two HAR datasets using accelerometer and gyroscope sensors from the smartphone device were evaluated, covering various daily human activities. An ensemble Random Forest (RF) was used as the base classifier to evaluate the performance of the hybrid algorithm. The performance was then compared with other shallow machine learning techniques such as Support Vector Machine (SVM), *k*-Nearest Neighbour (*k*NN), and Naïve Bayes (NB). One-versus-All (OvA) class binarization technique was adopted to enhance the detection of high-class correlations by converting initial problems of multiple classifications into a set of two-class classification problems. The proposed hybrid of Ensemble Filter with BHS-ABC for this research is capable of obtaining optimum feature subsets with high accuracy. The average of SBHAR and USCHAD datasets accuracy have improved by 3.2% and 1.6%, respectively, from the benchmark results.

ABSTRAK

Melalui kemajuan sensor boleh pakai, komunikasi tanpa wayar dan teknik pembelajaran mesin, Teknologi Bantuan (AT) untuk menyokong gaya hidup yang autonomi, aktif, dan sihat berkembang pada akhir-akhir ini. Di antara kemajuan ini, Pengecaman Aktiviti Manusia (HAR) adalah salah satu cara yang paling inovatif untuk menyokong atau mengawasi warga emas dalam kehidupan seharian mereka. Penyelidikan luas dalam bidang HAR juga penting untuk peningkatan kualiti kesihatan seseorang. Walau bagaimanapun, masalah ralat klasifikasi seperti variasi antara kelas (intra-class) dan pertindihan antara kelas dalam aktiviti yang sama (inter-class) mengurangkan ketepatan klasifikasi. Untuk meningkatkan pengecaman aktiviti manusia, ciri-ciri domain masa dan domain kekerapan digabungkan. Namun begitu, beberapa ciri yang diekstrak ini mungkin gagal menggambarkan aktiviti tersebut. Tujuan penyelidikan ini adalah untuk mencadangkan teknik pemilihan ciri hibrid untuk pengecaman aktiviti manusia yang optimum. Metodologi yang dicadangkan untuk penyelidikan ini adalah Penapis Gabungan (Relief-F dan mRMR) untuk memilih ciri-ciri yang paling relevan dan kurang berulang. Walaupun pendekatan ciri penapis biasa digunakan, kebanyakan penyelidikan tidak mengambil kira nilai had ambang untuk mengecualikan ciri-ciri yang tidak perlu dan berulang. Kemudian, algoritma Binari Carian Harmoni-Koloni Lebah Buatan (BHS-ABC) digunakan untuk menilai kualiti ciri-ciri yang dipilih. Dalam penyelidikan ini, dua dataset HAR yang menggunakan sensor pecutan dan sensor giroskop dari peranti telefon pintar akan dinilai, merangkumi pelbagai aktiviti harian manusia. Hutan Rawak (RF) digunakan sebagai pengelas asas untuk menilai prestasi algoritma hibrid. Prestasi pengelas asas dibandingkan dengan teknik pembelajaran mesin lain seperti Mesin Vektor Sokongan (SVM), k-Jiran Terdekat (kNN) dan *Naïve Bayes* (NB). Teknik binarisasi kelas Satu-lawan-Semua (OvA) digunakan untuk meningkatkan pengesanan korelasi kelas tinggi dengan menukar klasifikasi pelbagai kelas menjadi klasifikasi dua kelas. Teknik pemilihan ciri hibrid Penapis Gabungan dan BHS-ABC untuk penyelidikan ini mampu memperoleh subset ciri optimum dengan ketepatan tinggi. Ketepatan purata set data SBHAR dan USCHAD masing-masing meningkat sebanyak 3.2% dan 1.6% daripada hasil penanda aras.

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LIST OF ABBREVIATIONS

ABC	-	Artificial Bee Colony
ACO	-	Ant Colony Optimization
ADL	-	Activity of Daily Living
ANN	-	Artificial Neural Network
BA	-	Bat algorithm
BHS	-	Binary Harmony Search
BPSO	-	Binary Particle Swarm Optimization
CNN	-	Convolutional Neural Network
COA	-	Cuckoo Optimization Search algorithm
COAHS	-	Cuckoo Optimization Search-Harmony Search
FPA	-	Flower Pollination algorithm
GA	-	Genetic Algorithm
GBC	-	Genetic Algorithm- Artificial Bee Colony
HAR	-	Human Activity Recognition
HSABC	-	Harmony Search-Artificial Bee Colony
IB1		Instance-Based 1
IMU	-	Inertial Measurement Unit
IoT	-	Internet of Things
k-NN	-	*k*-Nearest Neighbour
LSSU	-	Local Search Symmetrical Uncertainty
mRMR	-	Minimum Redundancy Maximum Relevancy
NB	-	Naïve Bayesian
OOB	-	Out-Of-Bag
RF	-	Random Forest
SBHAR	-	Smartphone Based Human Activity Recognition
SU	-	Symmetrical Uncertainty
SVM	-	Support Vector Machine
USC-HAD	-	University of Southern California- Human Activity Dataset

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CHAPTER 1

INTRODUCTION

1.1 Overview

In recent years, Assistive Technology (AT) has made great strides by permitting older people or people with disability to perform tasks, which they have not been able to accomplish in the past. By definition, AT is a device or resource that facilitates the performance of tasks that are difficult or impossible for older adults or disabled persons. In older adults, such devices may be a walker to boost their balance, or amplifier to make it easier for people to listen. It might also include a magnification software for someone with a blind or reduced vision or a pushbike that helps them travel over distances that are too long to walk. In laymen's terms, AT is everything that helps humans to keep up with activities of daily living (ADLs). For some, the ability to perform simple daily tasks, such as walking and sitting, is considered essential. AT helps most people to live without long-term caring or home healthcare comfortably.

According (Chavarriaga *et al.*, 2010), there is a raising need for healthcare and AT technologies to design machine learning techniques that capable of dealing with the uncertainty prevalent in real-world implementations. Human Activity Recognition (HAR) is used mainly as an AT for older adults and healthcare in conjunction with other devices such as the Internet of Things (IoT) with the assistance of sensors, smartphones or pictures (Jobanputra *et al.*, 2019; Abdullah *et al.*, 2020; Alema Khatun and Abu Yousuf, 2020). The Internet of Things (IoT) is a growing area of technology which aims at connecting electronic monitors with vehicles, home appliances and also (mainly) people. For consumers, businesses and communities, IoT wearables are becoming increasingly popular.

Nowadays, sensors are embedded in many devices and generate signals in response to an event or activities. Sensors can be found in the physical world and in many electronic products, which is part of today's modern-day life. For example, wearable devices have sensors that generate signals in response to human activity, such as walking or running. Over the last few decades, numerous wearable sensors and devices have been developed with advances in design and computational power in signal processing. Wearable technologies are experiencing growing requirements and interests, especially in healthcare. For example, in defining health hazards, the volumes of information produced from wearable devices could be helpful.

The Human Activity Recognition (HAR) is used to enhance the quality of life of individuals in many applications. The objective of HAR is to acknowledge the user's actions and behaviours based on the setting and the sensed movement of the user. In particular, inertial HAR approaches use the Inertial Measuring Unit (IMU) to capture the motion of the user at a particular sensor location such as the wrist, ankle, or foot. With the development of sensor technology for micro-machine mechanical systems (MEMs), inertial sensors such as accelerometer, gyroscope, and magnetometers are developed and tested to perform activity recognition.

1.2 Problem Background

Human Activity Recognition (HAR) is a vast area of study that seeks to distinguish a person's specific gesture or action based on sensor data (Wang and Meng, 2018). This includes predicting a person's behaviour, which typically requires profound knowledge and techniques from signal processing to the required technical application from the raw data in order to conform to a machine learning model (Y. Wang *et al.*, 2017). The identification of human activity is considered as a challenging classification task in time series data. The misclassification of daily human activities remains one of the challenges in HAR (Wang *et al.*, 2018). A major contributing factor to this issue is due to different people behave differently for the same human daily activities such as 'walking' or 'running'. In HAR, intra-class variation happens when one activity category involves different styles of human motion. For example, in ‘walking’ activity, a person can walk very fast or slow. Furthermore, human activity similarities exist not only in different categories (intra-class variation) but also in the same categories (inter-class similarities). Inter-class similarities happened when the activity is physically different (e.g., walking downstairs and walking upstairs) but shows similar characteristics in sensor signal forms (Bulling *et al.*, 2014). These similarities would be challenging for intelligent machines to differentiate, thus contributes to the misclassifications.

The selection of features is another significant challenge since some features are less important which may not be useful in representing the activities. Time-domain features are often used to define static activities as a more generic, but useful one such as standing, and sitting (Zubair *et al.*, 2016; Arif *et al.*, 2017) Despite that, using these features alone to define the dynamic activities (e.g., walking and running) may not be precise (Shoaib *et al*., 2016). While the average accuracy obtained is good, an optimum number of features still have to be chosen to prevent dimensionality curses. Generally, selection strategies for features can be categorised into filter and wrappers.

The filter feature ranking approach was employed due to their less complicated nature and is capable of handling a vast number of instances (Bolón-Canedo *et al.*, 2014). Most of the research work, however, only based on selecting top-*k* features and did not define the threshold which discards the low-ranking feature (Doewes *et al.*, 2017; Amezzane *et al.*, 2018; Chandra, 2018; Abo El-Maaty and Wassal, 2019). Clearly, this method is not optimized since it is likely to overestimate or degrade the pruned features. There may also be some feature redundancies and a possible increase in the false detection rate.

Currently, metaheuristic-based optimization methods for solving optimization problems have been widely used in the research. A metaheuristic optimisation approaches such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC) and Harmony Search (HS) is used as the wrapper-based feature selection to select optimal feature subset. In comparison to the filter, wrapper methods use a classifier to maximize classification performance by choosing the relevant features as the learning algorithm. Metaheuristic algorithms aim primarily at avoiding drawbacks from iterative learning and the local optima issue in particular. Most of the metaheuristic algorithms are designed to solve a discrete or continuous optimization problem. Feature selection is regarded as a binary optimization problem, where solutions are restricted to binary values (Too *et al.*, 2018). Therefore, the binary version of the Harmony Search Algorithm (HSA) could be employed to solve this problem. However, metaheuristic algorithms such as HSA are likely to fall into local optima problems (Alia and Mandava, 2011; Yusup *et al.*, 2019; Li *et al.*, 2020).

1.3 Problem Statement

The presence of intra-class variation and inter-class similarity among distinct activities complicates activity recognition. When behaviours that are essentially dissimilar in nature (e.g., walking up and walking down) show remarkably similar sensor signal characteristics, this is referred to as inter-class similarity. While intra-class variation refers to an activity that involves various types of motion such as walking and running. The relationship exists because walking up and walking down are fundamentally different from other stride behaviours such as walking and running. The use of deep learning such as Convolutional Neural Network (CNN) has shown exceptional accuracy and the ability to distinguish behaviours with a high degree of inter-class similarity. Regrettably, due to the sensitivity of the lesser waveform, the CNN is incapable of generating high accuracy for static activity (Ronao and Cho, 2016).

Selecting the right features is complicated because some features are ineffective or even completely unnecessary for capturing the action. The time-domain features are commonly used because they are easier and more efficient for representing static behaviour. However, relying solely on these characteristics might not be sufficient to detect dynamic behaviour. Similarly, certain features may be redundant, which may increase the rate of false classification. While it achieved a reasonable level of accuracy on average, the number of features chosen is still very high. The benefits of using feature ranking methods to pick features are that they are less complex and can accommodate a large number of instances. However, the majority of works did not specify the feature boundary at which lower ranking features are discarded. By contrast, metaheuristic optimization techniques have been widely used to solve global optimization problems. When dealing with a large number of features, the computational cost of iteration and population re-evaluation for finding an ideal parameter has increased significantly.

Therefore, the problem statement for this research is,

A hybrid feature selection technique of the Ensemble Filter and Binary Harmony Search-Artificial Bee Colony (BHS-ABC) algorithm can select optimal features and recognize human activities for better classification accuracy.

Research questions of this work are as follows:

1. *How to reliably distinguish daily human activities for better recognition?*

Time-domain features were highly useful in discriminating between static activities like standing and sitting. On the other hand, the use of frequency-domain features is extracted to enhance the identification of dynamic activities. Time-domain features or statistical features are usually employed to distinguish the human activity especially for static or postural transition activities. However, if the frequency-domain features only are used, it could not produce high recognition performance, especially when distinguishing the static activity. Both feature categories (time and frequency domain) are, therefore, useful to distinguish between static and dynamic activities.

2. *How to select the most relevant and less redundant features based on the filter feature selection method efficiently?*

In filter feature selection, top-*k* features are usually employed to select the most top features rank (e.g., top 10, 50 features) based on the calculated and ranked feature weight. However, this practice is not an optimized technique since it could overestimate or underestimate the pruned features. Relief-F is an efficient feature ranking score; however, it cannot detect redundant features, which limits the application. Another filtering technique, Maximum Relevance Minimum Redundancy (mRMR), will then be used to discard these redundant features. mRMR attempts to pick a subset of features that correlate the most with a class (relevance) and the least with each other (redundancy). The selected feature subset based on the feature weight calculated from Relief-F will be the feature space for the mRMR algorithm. Then, a greedy search will be used by mRMR in order to find near-optimal features.

3. *How to find the optimal feature subset based on Binary Harmony Search-Artificial Bee Colony algorithm?*

While the BHS algorithm does not work in numerical optimisation in local search, the algorithm performance is good to identify the high-performance region of a solution space in a reasonable time. Because the ABC algorithm performs better in local and global optimisation, the binary HS algorithm hybridises by using the ABC algorithm to optimise the HS algorithm's Harmony Memory (HM). Harmony memory (HM) is a collection of the best solution and play a key role in the algorithm. ABC will be applied to optimize harmony memory as a learning mechanism. The harmony memory has considered food sources and is explored and exploited by the employed bees, the onlooker bees, and the scout bees. Then, a new harmony vector is generated in finding better solutions. If the newly improvised harmony is better, it will be stored in HM.

1.4 Aims and Objectives

This research aims to develop a hybrid filter-wrapper feature selection method using Ensemble Filter with BHS-ABC algorithm in order to get high classification accuracy with a minimal number of selected features, as shown in Figure 1.1

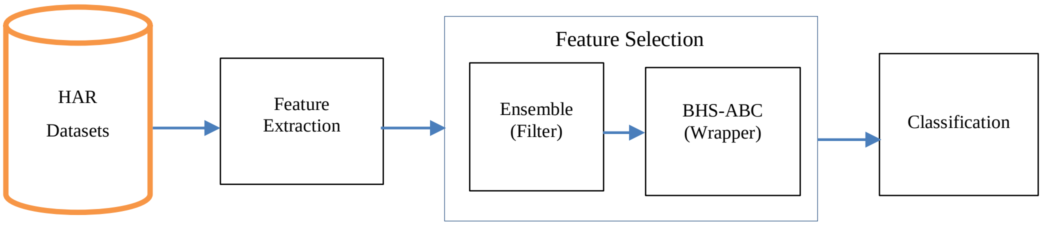

Figure 1.1 Research Aim

The objectives of this research are:

1. To fuse handcrafted time-domain and frequency-domain features for better recognition of daily human activities.
2. To develop an Ensemble Filter (Relief-F and mRMR) method to guide the search for the most relevant and less redundant feature subsets.
3. To develop a hybridization strategy by combining Ensemble Filter and Binary Harmony Search-Artificial Bee Colony algorithm for improving
4. recognition of intra-class variation and inter-class similarities activities.

1.5 Scopes of the Study

This research concentrates mainly on improving the identification of human activity behaviour, particularly when distinguishing related human activities. Two freely accessible physical activities datasets; SBHAR and USC-HAD been used in this research. These two datasets were chosen because they offer information about fundamental human behaviours, including static and dynamic activities. Additionally, the datasets were chosen because it utilised two sensors (accelerometer and gyroscope) within the Android smartphone and Inertial Measurement Unit (IMU), both of which are attached to a single position of the human's body. This thesis does not answer the issues under environmental conditions in real time.

In both data sets, different types of static and dynamic activities are included without focusing on the transition of two or more actions. The details of static and dynamic activities used in this research are available in Chapter 3. For each dataset the experiment is performed independently, and each experiment is compared with the experimental configurations of the selected research in the literature. The proposed feature selection is evaluated separately for each data set. The benchmark works from the literature are chosen and compared with the experimental result.

1.6 Significance of Research

This study is carried out to classify numerous human behaviours based on the reported data stream from an accelerometer and gyroscope sensors, as previously mentioned. This research primarily leads to an improved identification of intra-class variation and inter-class similarity of human behaviours by using a minimum number of features. The findings of this study contribute to the theoretical process of human activity recognition at the feature extraction, feature selection, and classification stages. In the feature extraction stage, a fusion of time-domain features and frequency domain features were utilized for a better recognition of daily human activities. In feature selection stage, a new Ensemble Filter (Relief-F and mRMR) method was developed where a threshold value was introduced in Relief-F to identify the optimal amount of feature subsets. Later, an ensemble filter was developed to eliminate redundant features using the mRMR algorithm. To improve the learning process of HM in BHSA, BHSA-ABC algorithm was developed. A new two-stage hybridization technique by combining Ensemble Filter with Binary HSA-ABC was developed to improve recognition of intra-class variation and inter-class similarities activities. Class binarization strategies of One versus All (OvA) with Random Forest (RF) algorithm was also employed in the classification stage. To help reduce the number of trees in the RF method, a self-adjusted tree was also implemented.

Human activity recognition has the potential to provide significant benefits to society, particularly in real-world such as aged and medical care. In the real world, smartphone-based evaluations have been proposed as a means of complacently monitoring gait and mobility in patients with early-stage Parkinson's disease. Patient or elderly people could benefit from a HAR system that monitors activity patterns and acts if something unusual happens, such as a change in behaviour. A HAR system may be able to help these people live more independently in the future.

1.7 Thesis organization

The thesis is made up of six chapters, each with a clear focus.

Chapter 1 provides a concise overview of activity recognition from a number of views. Furthermore, the latest trends and problems in activity identification have been analysed from numerous angles. The breadth and contribution of this research are described in this chapter, along with its limitations and research aims.

Chapter 2 details the prior work in the area of activity recognition, with specific information about the type of sensor utilised, as well as a description of earlier work using wearable sensors. Additionally, the approach of feature extraction and selection that is typically used to solve classification problems is presented.

The conceptual research framework approach for proposed better activity recognition is explained in Chapter 3. In the course of doing the activity recognition, some compulsory phases are implemented, including the pre-processing stage, the feature extraction stage, the feature selection stage, and the classification stage.

Chapter 4 discusses in depth the suggested feature selection approaches utilising Ensemble Filters (Relief-f and mRMR) with the BHS-ABC algorithm. The classification algorithms, which use OvA and OvO, have been developed to help separate activities with considerable intra-class variance from inter-class similarities.

The process and the results of the data's testing and analysis are outlined in Chapter 5. All experiments that are conducted in order to achieve the highest possible accuracy performance are analysed. The criteria for selection and the optimal parameter setting are discussed. The report also compares outcomes to previously published study.

Chapter 6 concludes the research by showing that the issue revealed in the research has been solved and is consistent with the stated objective. The report also includes a recommendation for future research based on the findings.

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