UNIVERSITI PUTRA MALAYSIA

HAND GESTURE CLASSIFICATION USING CONVEX HULL SKELETON JOINTS MOMENT K-NN TECHNIQUE FOR DIMENSIONALITY REDUCTION AND INCREMENTAL LEARNING IN THE CENTRAL NERVOUS SYSTEM'S HOLOGRAM

ZAINAL BIN ABDUL KAHAR

FSKTM 2022 2

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By

ZAINAL BIN ABDUL KAHAR

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ZAINAL BIN ABDUL KAHAR

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Chair : Puteri Suhaiza Binti Sulaiman, PhD
Faculty : Computer Science and Information Technology

Recent breakthroughs with numerous visual experiences using mobile devices encourage the research of human-computer interaction (HCI) involving hand gesture recognition for Holograms, Virtual Reality, and Augmented Reality. The rise of these technologies allows educators in medical segments to apply new pedagogy by interacting with virtual content in a coherent learning environment. In this thesis, the Central Nervous System (CNS) interaction is implemented using the Skeleton Joints Moment (SJM) approach for data reduction and convex hull k Nearest Neighbour (Convex Hull k-NN) for hand gesture classification. Principal Component Analysis (PCA) is commonly used for dimensional reduction as a data preprocessing for machine learning like k-NN, Support Vector Machine (SVM), and Artificial Neural Network. However, PCA implementation requires recalculation for a new batch of data. Therefore, this thesis presented the SJM CH k-NN with the Density Mapping to classify hand gestures in CNS application. Evaluation results show that this method supports incremental learning with optimized classification complexity than PCA k-NN, SVM, and ANN.

This thesis introduces SJM CH k-NN with Density Mapping that addresses three hologram interaction issues using low-end mobile devices. The issues are data dimensionality, the complexity of hand gesture classification for incremental learning, and the uncertainty of hand gesture classification within a class intersection.

First, this thesis proposed a robust centroid moment technique for hand gesture data to reduce k-dimensional space to achieve significant data reduction while retaining hand gesture information. SJM reduces k dimensional data from hand gesture skeleton data to three principal components (x, y, and z-axis). These components represent hand gesture moments. Researchers have proposed different methods of data reduction. One of the methods is PCA. PCA technique has similar accuracy compared to SJM. However, when new data is inserted, PCA must decompose the large datasets into a matrix of eigenvector and eigenvalue to describe their magnitude. Evaluation results using k-NN show that SJM has better accuracy than PCA for skeleton data. PCA has a higher uncertainty of mean error of 0.75 compared to SJM at only 0.01. In terms of accuracy, SJM shows 96% of prediction accuracy, similar to PCA using hand skeleton joints but with $O(n)$ complexity compared to PCA with $O(min(p^3, n^3))$ where n is the data points in the dataset, and p is the features.

Secondly, the importance and originality of this study are that it explores the complexity of hand gesture classification for incremental learning using a low-end device. Thus, this thesis presented a Convex Hull k-NN approach to optimize hand gesture classification complexity. The advantage of traditional k-NN is that it does not require preprocessing for a new batch of data. Many researchers have utilized k-NN to classify hand gestures in the past decades before moving to SVM and ANN. However, it is not practical for big data where the complexity is $O(n)$. The solution is to extend the Convex Hull method into k-NN. The k-value is the smallest intersected region of hand gesture classes. The evaluation result of the t-test shows that $P < 0.05$ where there is a significant difference between Convex Hull SJM and Convex Hull PCA. Thus, the SJM is feasible for Convex Hull SJM k-NN and has the complexity of classification of $O(c * log(c))$ for none intersected regions which is better than traditional k-NN $O(n)$ and ANN $O(nt * (ij + jk + kl))$ where i, j, k, and l are nodes, with t training examples and n epochs, and SVM $O(n^3)$. The experiment shows that SJM CH k-NN optimized computational complexity by $O(c + i * log(c + i))$ for an incremental dataset in a real-time environment with high accuracy of 98% where c is the convex hull points.

Finally, the third aim of this study is to investigate the uncertainty of hand gesture classification. The primary concern of Convex Hull SJM k-NN is the intersected region of the convex hull. Therefore in this thesis, density mapping for the intersected convex hulls is introduced in the CNS system. Using Convex Hull SJM k-NN with density mapping reduces 76% of data. The t-test result shows that SJM data and SJM Density Mapping data have a significant difference of $P < 0.05$. The F1 score results of this experiment show that Convex Hull SJM k-NN with Density Mapping has 94% of accuracy. The results indicate that Density Mapping reduces the data size into a fixed data frame for intersected convex hulls.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia
Sebagai memenuhi keperluan untuk ijazah Doktor Falsafah

KLASIFIKASI GERAK TANGAN MENGGUNAKAN TEKNIK k-NN DENGAN CEMBUNG RANGKA SENDI UNTUK PENGURANGAN DIMENSI DAN PEMBELAJARAN MESIN BERTAMBAH DALAM HOLOGRAM SISTEM SARAF PUSAT

Oleh

ZAINAL BIN ABDUL KAHAR

Januari 2022

Pengerusi : Puteri Suhaiza Binti Sulaiman, PhD
Fakulti : Sains Komputer dan Teknologi Maklumat

Penemuan terkini dengan pelbagai pengalaman visual menggunakan peranti mudah alih menggalakkan lagi penyelidikan interaksi manusia-komputer (HCI) yang melibatkan pengecaman isyarat tangan untuk tujuan interaksi Hologram, Realiti Maya dan Realiti Berperantara. Kebangkitan teknologi ini membolehkan pendidik di dalam segmen perubatan untuk menerapkan pedagogi baharu dengan berinteraksi melalui kandungan maya di dalam persekitaran pembelajaran yang koheren. Dalam tesis ini, interaksi Sistem Saraf Pusat (CNS) dilaksanakan menggunakan pendekatan *Skeleton Joints Moment* (SJM) untuk pengurangan data dan *Convex Hull k Nearest Neighbour* (CH k-NN) untuk klasifikasi isyarat tangan. Analisis Komponen Utama (PCA) biasanya digunakan untuk pengurangan dimensi sebagai prapemprosesan data untuk pembelajaran mesin seperti k-NN, Mesin Vektor Sokongan (SVM) dan Rangkaian Neural Buatan. Walaubagaimanapun, pelaksanaan PCA memerlukan pengiraan semula untuk kumpulan data baharu. Oleh itu, tesis ini membentangkan SJM CH k-NN dengan pemetaan kepadatan untuk mengklasifikasikan isyarat tangan dalam aplikasi CNS. Keputusan penilaian menunjukkan bahawa kaedah ini dapat mengoptimumkan kerumitan klasifikasi berbanding PCA k-NN, SVM dan ANN.

Tesis ini memperkenalkan SJM CH k-NN dengan Pemetaan Ketumpatan yang menangani tiga isu interaksi hologram apabila menggunakan peranti mudah alih berkuasa rendah. Isunya ialah saiz dimensi data, kerumitan klasifikasi di dalam pengecaman isyarat tangan untuk pembelajaran mesin yang mem-

punyai kemasukan data berperingkat, dan ketidakpastian klasifikasi dalam kelas-kelas isyarat tangan yang bertindih.

Pertama, tesis ini mencadangkan teknik momen tengah untuk isyarat tangan bagi mencapai pengurangan data yang ketara sambil mengekalkan maklumat isyarat tangan tersebut. SJM mengurangkan dimensi data daripada rangka isyarat tangan kepada tiga komponen utama iaity paksi x, y dan z. Komponen ini mewakili isyarat tangan. Penyelidik di dalam bidang ini telah mencadangkan kaedah yang berbeza melibatkan pengurangan data. Salah satu kaedahnya ialah PCA. Teknik PCA mempunyai ketepatan yang sama apabila dibandingkan dengan SJM. Walaubagaimanapun, apabila data baharu dimasukkan, PCA mesti mengambil semula set data lama untuk diproses semula menjadi matriks vektor eigen dan nilai eigen untuk mendapatkan magnitudnya. Keputusan penilaian menggunakan k-NN menunjukkan bahawa SJM mempunyai ketepatan yang lebih baik daripada PCA untuk data rangka. PCA mempunyai ketidakpastian minimum ralat yang lebih tinggi iaitu 0.75 berbanding SJM yang hanya 0.01. Dari segi ketepatan, SJM menunjukkan ramalan yang sama berbanding PCA iaitu 96% tetapi mempunyai kerumitan yang lebih optimum iaitu $O(n)$ manakala PCA dengan kerumitan $O(min(p^3, n^3))$ dimana n ialah jumlah data di dalam set data dan p ialah ciri-ciri data.

Kedua, kepentingan kajian ini ialah untuk meneroka kerumitan klasifikasi isyarat tangan untuk pembelajaran mesin tambahan menggunakan peranti berkuasa rendah. Oleh itu, tesis ini mencadangkan pendekatan *Convex Hull k-NN* (CH k-NN) untuk mengoptimumkan kerumitan klasifikasi isyarat tangan. Kelebihan k-NN tradisional ialah ia tidak memerlukan prapemprosesan untuk kumpulan data baharu. Ramai penyelidik telah menggunakan k-NN untuk mengklasifikasikan gerak isyarat tangan dari dulu lagi sebelum beralih ke SVM dan ANN. Walaubagaimanapun, ia tidak praktikal untuk data besar yang kerumitannya ialah $O(n)$. Penyelesaiannya ialah dengan menambah pendekatan *Convex Hull* ke dalam k-NN. Nilai k ialah kawasan berntindih terkecil bagi kelas-kelas isyarat tangan. Keputusan penilaian t-test menunjukkan $P < 0.05$ di mana terdapat perbezaan yang signifikan antara *Convex Hull* SJM dan *Convex Hull* PCA. Oleh itu, SJM boleh digunakan untuk perlaksanaan CH k-NN yang mempunyai kerumitan pengelasan $O(c * log(c))$ untuk kawasan tidak bersilang dimana ia lebih baik daripada k-NN tradisional $O(n)$ dan ANN $O(nt * (ij + jk + kl))$ diaman i, j, k dan l ialah nod, t adalah data contoh, dan SVM $O(n^3)$. Penilaian menunjukkan bahawa SJM CH k-NN mengoptimumkan kerumitan kepada $O(c + i * log(c + i))$ untuk set data tambahan dalam persekitaran masa nyata dengan ketepatan 98% dimana c ialah jumlah data dari pemprosesan *Convex Hull*.

Akhir sekali, matlamat ketiga kajian ini adalah untuk menyiasat ketidakpastian klasifikasi isyarat tangan. Masalah utama di dalam perlaksanaan SJM

CH k-NN ialah kawasan bersilang pada kelas-kelas *Convex Hull*. Oleh itu tesis ini mencadangkan pemetaan ketumpatan untuk *Convex Hull* bersilang yang akan diguna pakai di dalam sistem CNS. Menggunakan SJM CH k-NN dengan pemetaan ketumpatan mengurangkan 76% data. Keputusan t-test mendapati data SJM dan data pemetaan kepadatan SJM mempunyai perbezaan yang signifikan iaitu $P < 0.05$. Keputusan skor F1 menunjukkan bahawa SJM CH k-NN dengan pemetaan ketumpatan mempunyai 94% ketepatan. Keputusan menunjukkan bahawa pemetaan ketumpatan mengurangkan saiz data untuk *Convex Hull* yang bersilang.

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This thesis was submitted to the Senate of Universiti Putra Malaysia and has been accepted as fulfilment of the requirement for the degree of Doctor of Philosophy. The members of the Supervisory Committee were as follows:

Puteri Suhaiza Binti Sulaiman, PhD
Associate Professor
Faculty of Computer Science and Information Technology
Universiti Putra Malaysia
(Chairman)

Fatimah Binti Khalid, PhD
Associate Professor
Faculty of Computer Science and Information Technology
Universiti Putra Malaysia
(Member)

Azreen Bin Azman, PhD
Associate Professor
Faculty of Computer Science and Information Technology
Universiti Putra Malaysia
(Member)

Hizmawati binti Madzin, PhD
Senior Lecturer
Faculty of Computer Science and Information Technology
Universiti Putra Malaysia
(Member)

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LIST OF ABBREVIATIONS

ANN	Artificial Neural Network
CNS	Central Nervous System
HCI	Human Computer Interaction
IL	Incremental Learning
KNN	k Nearest Neighbour
ML	Machine Learning
PCA	Principal Component Analysis
SJM	Skeleton Joints Moment
SVM	Support Vector Machine

CHAPTER 1

INTRODUCTION

Neuroscience students in pharmacotherapy, pharmacology, and pathophysiology mainly study the central nervous system. It is for medical conditions and complications. Universiti Putra Malaysia academicians in neuroscience suggest that central nervous system holograms can make teaching and learning easier by embracing the idea of hybrid learning. It may help to enable interactive visualization, brings conceptual clarity, and ensures communication efficiency between educators and the students. However, most academicians have low-end devices and minimal internet accessibility. Low-end devices have a stringent resource constraint compared to high-end devices to recognize interaction due to limited computational power, memory, and power supply, e.g., mobile devices and tablets (Hahm et al., 2016). Therefore, this thesis explicitly studies the constraints of the human-computer interaction (HCI) approach for low-end devices. The HCI functionality is to navigate the central nervous system within a hologram environment.

HCI using machine learning can be used to support various low-end devices. It is vital in optimizing interaction complexity for mobile devices packed with running sensors and visual experience. There are many sectors in education that practice human interaction for training purposes. The training takes place in a virtual environment. One of the most common interactions in Augmented Reality (AR), Virtual Reality (VR), Mixed Reality (MR), and a hologram is hand interaction. The hand interaction of virtual objects is implemented using machine learning approaches to recognize hand gestures that can be conducted using hand shapes or skeleton joints. A skeleton joint for hand gesture representation contains connections between all joints connecting neighboring phalanges. A dynamic hand gesture could be analyzed from the skeleton joints if a hand pose changed to predict which gesture is being performed (Shin and Kim, 2020). The HCI practiced by the educational sector has improvised pedagogy of the conventional system to be more interactive (Ramsundar, 2015). Due to digitization, interaction data across the virtual environment uncovers the hand gesture patterns using machine learning algorithms (Reddy et al., 2020). It provides a new challenge in HCI, for instance, hand gesture classification using incremental learning (Yang and Liao, 2014). The challenge in incremental learning is to retrain these interactions to accommodate new, previously unseen data, which demands high computational time and energy requirements (Sarwar et al., 2020). Besides, the large data dimension is difficult to classify (Lv et al., 2020). This study intended to use hand gesture classification using incremental learning and hologram pyramid for Central Nervous System (CNS) application where medical students can view and interact with 360-degree hologram objects. This approach will help the student visualize the complex human nerve system interactively. It is one of the most challenging topics in human anatomy.

An interactive holographic CNS application includes predetermined navigation throughout the complete nervous system as visual objects. The visual objects being displayed are the brain and the spinal cord, as shown in figure 1.1. The brain that makes up the large portion of the nervous system is divided into four parts (Brainstem, Cerebellum, Diencephalon, and Cerebrum) and connects with the vertebrae. The vertebrae, consisting of cranial nerves from the brain, protects the spinal cord. A more detailed explanation of CNS is given in chapter 2.

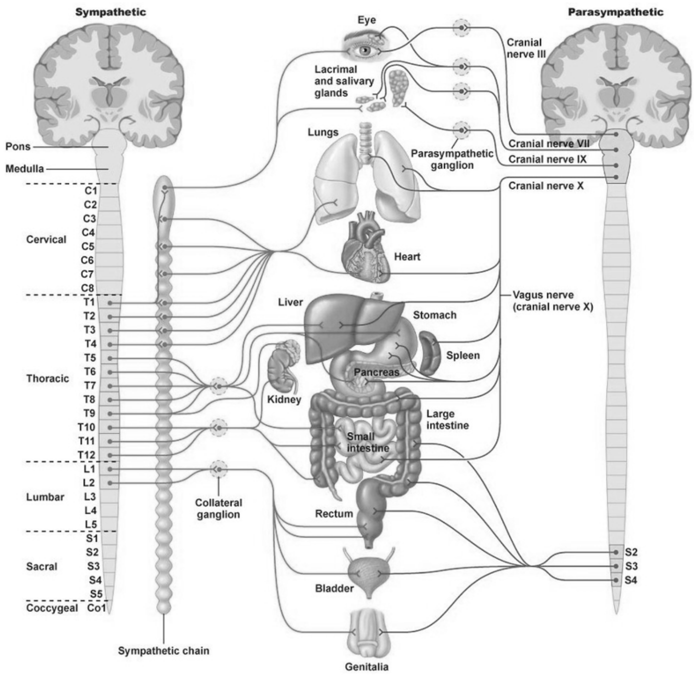

Figure 1.1: Central nervous system

In this study, the CNS application aims to create virtual immersion content with real-time interaction in a hologram environment. Educators can use the pyramid hologram projection to interact with the brain using intuitive free-hand gestures (Cheng et al., 2016). Hence, hand gestures have become the principal technology for realizing immersive virtual interaction (Rosedale, 2017).

The CNS application uses hand gesture interaction to interact with the brain in a hologram setup. Hand gesture interaction is a way for a computer to start comprehending human non-verbal communication. The general meaning of hand gestures is the capacity of a computer to identify motions and execute orders dependent on those gestures (More and Sattar, 2016). In addition, hand gestures are ubiquitous, are natural characteristics, and are a significant part of communication. Many studies have claimed that a hand gesture is a structured system during human cognition and interaction (Yao and Fu, 2014). It is tactile, familiar to users, precise, and comfortable to use (Xiao et al., 2018). Hence, hand gesture study is vital in the progression of computer vision.

Hand gesture is an effective technique for hologram human-computer interaction (HCI). The main objective of this study is to make the interaction between human and hologram interface as natural as possible. Like VR, AR, and MR, hand gestures are the most suitable way to interact with 3D (Sonkusare et al., 2015). With the advancement of virtual peripherals and sensors, hand gestures have become a well-known approach to interacting with head-mounted devices, tablets, and hologram projection. Users can control it without physically touching a screen, using a keyboard or mouse. Therefore, HCI has become a vital study for pattern classification in computer vision fields (Yao and Fu, 2014)(Quan and Liang, 2017).

Hand gesture classification involves statistical learning theory and activation control schemes. The standard approach of predictive pattern recognition in machine learning like SVM, k-NN, and ANN emphasizes the minimization of empirical risk (Pasolli et al., 2011). An SVM-based classification system provides excellent performance like traditional classifiers. It is strongly influenced by the quality and quantity of the segmentized labeled data used to train the classifier. A k-NN method is a popular data mining and statistics classification approach due to its simple implementation and significant classification performance (Zhang et al., 2008). However, assigning a fixed k value to all test samples is impractical for traditional k-NN methods, even though set by experts. For artificial neurons called Artificial Neural Networks (ANNs) or Synthetic Neural Networks (SNNs), a neural network (NNs) is an integrated collection of artificial human neurons utilizing a mathematical or computational model for information processing based on a connectionist approach to computation. An artificial neural network reveals that a good choice of activation functions and control scheme will lead to a high memory capacity and increased pattern retrieval capabilities (Lin and Chen, 2009).

Segmentizing data for hand gesture classification is required to divide labels belonging to a particular hand gesture class by any scoring parameter from hand features defining their likeliness to belong to that specific class (Mohapatra, 2019). Data labeling is computationally costly. Many researchers in their study use Convex Hull to reduce the number of samples for classification (Xu et al., 2021). Convex Hull reduces sample by vertices selection (Ding et al., 2018).

Machine learning classification has been applied with the moment's approach in various applications. It is due to their invariant features and regardless of the variations imposed (Zhihu Huang and Jinsong Leng, 2010) (Alp and Keles, 2017). Pasolli et al. applied hand gestures as an approach to interacting with virtual content using HU Moments and SVM to achieve real-time recognition (Pasolli et al., 2011). Monge et al. (Monge-Álvarez et al., 2019) claimed that by using the Hu Moments approach, the system he developed could detect audio-cough up to 88.51% for high sensitivity and 99.77% for specificity. Lopez et al. described classifying five genres using Hu Moments led to the accuracy of 83.33% (Lopes et al., 2017). Shen et al. experiment results show that Hu Moments can eliminate a large amount of noise (Shen et al., 2015). Moment's approach could therefore classify and recognize the geometrical features of the hand interaction. Plawiak et al. used k-NN to classify hand body language gestures from specialized glove (Pławiak et al., 2016). Dembi et al. from the University of Columbia used ANN to solve the inverse kinematic computational problem in robotics. This seemingly simple task is required to decide how to transform each joint to achieve the desired pose in cartesian coordinates (Demby'S et al., 2019).

Machine learning involves high-dimensional data, which consists of many features during data collection. There are potential issues when the data is high in dimension. The first issue is the risk of massively overfitting the machine learning model and reducing sample performance. It causes the classification to be harder to cluster among the classes and appear equally alike and prone to uncertainty. Hence, dimensionality reduction can remarkably reduce the complexity during training and classification phases (Reddy et al., 2020) (Zhang et al., 2008).

1.1 Motivation

Hand gesture recognition is becoming crucial for virtual interaction in a hologram, virtual reality, augmented reality, and mixed reality. However, the hand gestures classification requires high computation and is unsuitable for real-time prediction and incremental learning. Another alternative is to obtain cloud computing. However, it takes time to process new data with limited resources. It requires expertise in cloud computing and is limited to a good sample of data. It is hard for an educator with low-end devices without access to the cloud to apply hand gesture prediction in a classroom without high-end computing. Moreover, there will be an issue when educators for medical require a custom pose that is not in the cloud. The list below are the issues in hand gestures classification for CNS application:

- The CNS application aims to run on low-end tablets. The experiment on hand gesture classification lagged for every new batch of data using the device. Current solutions like k-NN, SVM, and ANN require high computation to remodel the class of hand gestures, which causes the lag. Hence, it motivates this study to find an approach to reduce the number of samples for classification.

- The incremental machine learning for a large dataset requires constant and stable access to cloud computing. However, the CNS application was not configured to operate within cloud computing due to the mobile teaching environment, where internet access was limited.

- Other than limited internet access, the teaching environment was in an offline mode most of the time. Therefore, an offline CNS application with high dimensional data reduction is proposed to cover various teaching environments.

1.2 Problem Statements

1.2.1 High dimensional hand gesture data in a low-end device to use machine learning

Classification of hand gestures using machine learning in low-end devices is computationally expensive for high-dimensional data and consists of unnecessary features. SVM and ANN are computationally expensive during training or classification of hand gestures with high dimensional data (Rzayev et al., 2017). In his paper, Musetta claimed that numerical simulations using ANN for complex structures require time-consuming computation (Mussetta et al., 2009). Therefore, the performance strongly depends on the hardware. Hand gesture recognition using SVM with a large dataset is a challenging problem and requires a growing memory with the number of training samples (Wang, 2008). Over the past decade, most data reduction research has emphasized PCA usage. PCA result indicates data reduction from 1246 to 38 from the collected hand skeleton data. However, these methods require remodeling for every new batch of data. Therefore, a preprocessing solution without remodeling is needed to reduce the number of samples to smaller dimensions.

1.2.2 Training and prediction complexity with incremental learning for low-end devices

The main challenge many researchers face is the significant amount of computational complexity for incremental learning in low-end devices. This challenge leads researchers to find the best method to retain the trained data when a new batch of data arrives. However, most of the incremental learning approaches require time to update. It is also cumbersome to collect and annotate the training data (Guo et al., 2019). In a standard SVM, the training process has $O(n^3)$ time complexities, where n is the size of the training dataset (Wang, 2009). The neural network complexity for classification is $O(nt * (ij + jk + kl))$, where i is the number of nodes, j number of nodes in the second layer, k in the third layer, and l is the output layer. It is mainly concerned with learning models in an ever-changing environment (Bouchachia et al., 2007). The traditional approach of learning model using all the data at once may not be feasible because it may require more storage for growing data and take a very long time to build. Furthermore, the one-time built model may not be able to learn the changed patterns automatically over time (Pesala et al., 2019). Hence, a new method is necessary to resolve this issue.

1.2.3 Complexity of class intersection

Uncertainty of hand gestures when classes intersect is one of the most frequently stated problems in machine learning. The complexity of uncertainty requires high-performance processing during classification when the data size is growing (Samadpour et al., 2015) (Jiaqi and Chung, 2017). The intersected class region in this study becomes computationally expensive, and the class becomes uncertain. It tends to search the nearest neighbors for a target in the entire training set (Hou et al., 2018). For that reason, this study needs a new approach to reduce data in intersected hand gesture classes.

1.3 Goal and Objectives

This study aims to develop a hand gesture classification model for low-end devices. This research used data reduction and a fast machine learning algorithm named SJM Convex Hull k-NN. It reduces the complexity of hand gesture classification in a real-time environment without the preprocessing of the dataset after the data reduction. The following objectives are the solution to accomplish the goal:

- To reduce data dimension of hand gesture dataset without preprocessing for growing data using skeleton joints moment.
- To design incremental learning using a Convex Hull k-NN approach to reduce the complexity of training and prediction for incremental learning.
- To optimize the searching complexity of an intersected cluster of classes that cause uncertainty during classification.

1.4 Scope of research

This research aims to implement the SJM, CH k-NN, and Density Mapping method on a hologram CNS application. The requirement is to prevent recalculation of the new batch dataset in an offline environment. Therefore, this research examines a non-reverse technique such as moments and k-NN using skeleton features as a dataset from a hand tracking device. The proposed SJM CH k-NN with Density Mapping implementation is specifically for tablet and desktop applications. Hence, CNS application implementation on a mobile devices such as Android and iOS smartphones is not under the scope.

1.5 Thesis organization

The thesis has four main parts: the introduction, literature review, research chapters, and conclusion. The overview of the thesis organization is as follows:

Part I – Introduction

Chapter 1 is an introductory chapter that explains the research motivation, then clarify the problem statements, goal and objectives, and the scope of the research.

Part II – Literature Review

Chapter 2 discussed the related studies, starting with an overview of data reduction techniques used in hand gesture classification and focusing on the SJM technique. Then, the chapter continues to cover the data reduction techniques related to high dimensional data, machine learning, and the MapReduce method that constitute this thesis.

Part III – Research Chapters

This part consists of 4 chapters. Chapter 3 explains the overall research framework, and the following chapters elaborate on the separate study related to each research objective. Chapter 4 details the SJM data reduction, Chapter 5 explains the CH kNN, and Chapter 6 describes the Density Mapping. Chapter 4, Chapter 5, and Chapter 6 consist of an introduction, methodology, experiment, results, and discussion.

Part IV – Conclusion

Chapter 7 provides the conclusions of each research chapter related to the research objectives, followed by clarifying the research contributions of this thesis. Finally, this study recommends future works at the end of the chapter.

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