CLASSIFYING INDIAN CLASSICAL DANCES BY MOTION POSTURE PATTERNS

By:

KHOR CHONG HWA

(Matrix No.: 128939)

Supervisor:

Dr. Loh Wei Ping

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Universiti Sains Malaysia

DECLARATION

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ABSTRAK

Tarian adalah suatu bentuk pergerakan manusia klasik yang biasanya dipersembahkan sebagai reaksi terhadap muzik. Misalnya, tarian klasik India memerlukan pergerakan yang rumit yang berkait dengan postur pergerakan tubuh dan isyarat tangan dengan persamaan yang tinggi. Kajian lepas menunjukkan minat dalam menggunakan pelbagai kaedah untuk mengklasifikasikan tarian-tarian. Kaedah yang paling biasa digunakan ialah Model Markov Tersembunyi (HMM) selain daripada menggunakan kaedah korelasi matriks dan analisis kluster hierarki. Walau bagaimanapun, kurang usaha yang dilakukan untuk menganalisis tarian India dengan menggunakan pendekatan perlombongan data. Oleh itu, objektif kajian ini adalah untuk (i) membezakan pelbagai jenis tarian klasik India, (ii) mengklasifikasikan jenis tarian berdasarkan corak postur gerakan dan (iii) menentukan kesan atribut untuk ketepatan pengelasan. Kajian ini melibatkan lima jenis tarian klasik kaum India (Kathak, Bharatanatyam, Kuchipudi, Manipuri dan Odissi). Pendekatan perlombongan data digunakan untuk pengelasan corak postur gerakan mengikut jenis tarian. Sebanyak 15 video tarian dikumpulkan daripada domain umum untuk proses pengesanan sendi badan dengan menggunakan perisian Kinovea. Analisis perlombongan data dilakukan pada tiga peringkat: pra-pemprosesan data, klasifikasi data dan penemuan pengetahuan dengan menggunakan perisian WEKA. Algoritma RandomForest mencatatkan ketepatan klasifikasi yang tertinggi (99.2616%). Pada konfigurasi atribut, koordinat-y pergelangan tangan kiri (LW (y)) telah dikenal pasti sebagai sifat yang paling penting untuk membezakan kelas tarian klasik India.

ABSTRACT

Dance is a classic form of human motion which is usually performed as a reaction of expression to music. The Indian classical dances, for instance, require multiple complicated movements that relates to body motion postures and hand gestures with high similarities. Past studies showed interests using various methods to classify dances. The most common method used is the Hidden Markov Models (HMM), apart from using the correlation matrix method and hierarchical cluster analysis. Nevertheless, less effort has been placed in analysing the Indian dance by using the data mining approach. Therefore, the objectives in this work are to (i) distinguish different types of Indian classical dances, (ii) classify the type of dance based on motion posture patterns and (iii) determine the effects of attributes on the classification accuracy. This study involves five types of Indian classical dances (Kathak, Bharatanatyam, Kuchipudi, Manipuri and Odissi) motion postures. The data mining approaches were used to classify the motion posture patterns by type of dances. A total of 15 dance videos were collected from the public available domain for body joints tracking processes using the Kinovea software. Data mining analysis was performed in three stages: data pre-processing, data classification and knowledge discovery using the WEKA software. RandomForest algorithm returned the highest classification accuracy (99.2616%). On attribute configuration, y-coordinates of left wrist (LW(y)) was identified as the most significant attribute to differentiate the Indian classical dance classes.

CHAPTER 1

INTRODUCTION

1.0 Introduction

Dance is sequence of expressive human body movement and has aesthetic values.(Anbarsanti & Prihatmanto, 2014). Some dances even involve complicated movements that relates to body motion postures, orientations and hand gestures. Certain classical dances have high similarities between each other which are difficult to differentiate from its joints coordinate postures. The analysis of classical dance motion later emerges to observe the patterns of classical dance types. Among the popular interests is the classical India dances. Indian classical dances were formed on complex body signatures produced from rotation, bending, and twisting of fingers, hands, and body (Kumar & Kishore, 2017).

In previous studies, various methods were used to classify dances. The most common method used is the Hidden Markov Models (HMM). HMM is considered an effective and efficient method for classifying of dances. Besides, past studies also depend on the correlation matrix to analyse differences in dance motion. Another commonly reported approach is the hierarchical cluster analysis. The Adaboost Multiclass Classifier, histogram of oriented (HOG) feature, support vector machine (SVM) and convolutional neural network (CNN) were used for classifying Indian classical dances. Existing work attempted classification of dance patterns and gestures by various techniques, however there are lack of works that adopted the data mining approach. The digital understanding of Indian classical dance is the least studied work, though it has been a part of Indian Culture from around 200BC (Kumar & Kishore, 2017). Therefore, this study will focus on applying the data mining approach for categorizing the motion patterns of Indian classical dances.

In this study, markerless video sources on five different types of classical Indian dances namely Kathak, Bharatanatyam, Kuchipudi, Manipuri and Odissi will be extracted from the YouTube publicly available domain. There were three videos selected for each type of dances. The raw video data will be transformed into images followed by translation into numeric data using the Kinovea software. There was a total of five body joints tracked at different time steps that include the forehead, right wrist, left wrist, right ankle and left ankle. All the joints were traced using markers in Kinovea software. The raw data were pre-processed in the Weka software in order to identify and remove potential outliers and extreme values. The cleaned data were then classified into five dance classes using all built-in algorithms in Weka tool on 10-fold cross validation. The significant attributes were examined to investigate impact of 20 study attributes: x-coordinates for forehead [F(x)], y-coordinates for forehead [F(y)], time frame for forehead [F(t)], motion speed for forehead [F(s)], x-coordinates for right wrist [RW(x)], y-coordinates for right wrist [RW(y)], time frame for right wrist [RW(t)], motion speed for right wrist [RW(s)], x-coordinates for left wrist [LW(x)], y-coordinates for left wrist [LW(y)], time frame for left wrist [LW(t)], motion speed for left wrist [LW(s)], x-coordinates for right ankle [RA(x)], y-coordinates for right ankle [RA(y)], time frame for right ankle [RA(t)], motion speed for right ankle [RA(s)], x-coordinates for left ankle [LA(x)], y-coordinates for left ankle [LA(y)], time frame for left ankle [LA(t)] and motion speed for left ankle [LA(s)] on the accuracy of dance classification. The classification error analysis was subsequently applied to determine the cause of misclassifications.

1.1 Project Background

There are various types of Indian classical dances in India. The popular ones are Kathak, Bharatanatyam, Kuchipudi, Manipuri and Odissi. Although every dance form evolved from different regions, but their origins are the same. Although these dances have their own uniqueness, but they have great similarities which are difficult to differentiate. For instance, the same 'mudras' or signs of hand gestures as a common language of expression ("Indian Classical Dances - Traditional Dances Of India," 2018). The joints coordinates are major aspects to describe motion postures. Therefore, this research considers the five joint coordinates (forehead, right wrist, left wrist, right ankle and left ankle) for classification analysis.

It is interesting to examine if body movements and gestures can distinguish types of Indian dances. It is noteworthy to adopt data mining approach to study the joints coordinate in order to describe motion postures by time steps in different dances.

This project analyses on 15 publicly available Indian classical dance videos to track the motion speed and joints coordinates of dancers for classification. In the first step of data mining, collected data undergo pre-processing analysis which involves data transformation and data cleaning analysis. Kinovea software will be used to transform video to image and followed by the image to numeric data. Videos of time steps from range 634 to 848 were snapshots at 25fps for static images. The static images were hold to track the speed and body joint coordinates of dancers. The body joints which include forehead, right wrist, left wrist, right ankle and left ankle will be marked by using markers in Kinovea software. The WEKA software will also be used to aid in data mining analysis at data pre-processing, data classification, significant attribute analysis and classification error analysis stages. Pre-processing analysis was performed to identify and remove the outliers and extreme values from the raw data into pre-processed data state. In order to classify the data, 10-fold cross validation classification was used to categorize pre-processed data into five classes of dance types: Kathak, Bharatanatyam, Kuchipudi, Manipuri and Odissi. Classification reliability for algorithms will be tested by comparisons with the zeroR accuracy. This was followed by significant attribute analysis and classification error analysis to identify the effect of attributes and to determine the cause of misclassification.

The expected outcome from the project are to distinguish different types of Indian classical dances based on motion posture patterns.

1.2 Problem Statement

There are some close similarities among different Indian classical dances which are difficult to distinguish. There were many studies conducted to analyse different type of dances. For example, Greek dance, Japanese dance and Indonesian dance are the popular dance investigated by the dance researchers based on classification approach. However, few studies have focused on Indian classical dances. Another lacking in dance study was that no effort has been placed in analysing the Indian dance by using the data mining approach. Specifically, there is no reported work that applied Kinovea software and Weka tool as auxiliary applications to classify Indian classical dances.

1.3 Objectives

The goals of this project are to

(i) distinguish different types of Indian classical dances.

(ii) classify the type of dance based on motion posture patterns.

(iii) determine the effects of attributes on the classification accuracy.

1.4 Scope of Work

This study applies data mining approaches to categorize the type of dance by classifying the motion posture patterns described by body joints coordinates recorded by time steps. There are five types of classical Indian dances involved for the case study analysis. The types of dances are Kathak, Bharatanatyam, Kuchipudi, Manipuri and Odissi which will be retrieved from public available domain of YouTube. The videos were imported into Kinovea software to track the motion joint coordinates and transform all images into numeric measurements. The data measured include body joint coordinates, time step, movement distance along with its derived quantities, the speed. Classification analysis is performed on seven classifiers: bayes, function, lazy, meta, misc, rules and trees using the embedded 41 algorithms in WEKA tool. The most appropriate algorithm will be selected and applied for further significant attribute and classification error analyses.

1.5 Thesis Organization

This thesis was structured into five main chapters which includes introduction, literature review, research methodology, results and discussion and the conclusion and future work.

In the first chapter, the overview of the work was presented. The subsections for introduction chapter include project background, problem statement, objectives, scope of work and thesis organization.

The second chapter presents the literature review. A review on previous studies related to classification techniques, pattern recognition and dance motion analysis in dance studies were presented.

Next, in the research methodology chapter, the main content is the approaches to classify the Indian classical dances into five dance classes: Kathak, Bharatanatyam, Kuchipudi, Manipuri and Kathak. Classification analysis was based on motion posture patterns described numerically by the body joint coordinates recorded at different time steps.

As for chapter 4, the results obtained from classification and knowledge discovery analysis were presented and discussed.

The last chapter conclude the overall findings from the study. Besides, the contributions of the study and what can be extended for the future work were presented.

CHAPTER 2

LITERATURE REVIEW

2.0 Overview

This chapter presents the review of previous studies related to classification techniques, pattern recognition and dance motion analysis. Majority past studies were focused on the classification techniques while others put emphasis on the pattern recognition and dance motion analysis. The background, strengths and weaknesses from the reported works were addressed.

2.1 Search strategy

All the previous related studies were searched by using the strategy of filtering in journal search engines: IEEE Xplore, ScienceDirect, Researchgate and ELSEVIER. At first, two keywords which were dancing data mining and classification of dancing data mining were searched to determine the number of related papers. Then, the number of papers were further filtered by years, followed with filtered by years and article type, and lastly filtered by years, article type and access type. The statistical values are as shown in Table 2.1. After applying several levels of filtering, the number of related papers for both keywords were reduced to 106 papers and 44 papers. After reviewed and revised through all the related papers, there are 21 papers which are appropriate and related to this study.

Table 2.1: Statistical values for related papers after applied search strategy.

Filter method	Keywords	Number of related papers
Without filter	Dancing data mining	3439
	Classification of dancing data mining	1390
Filter by years (2005-2019)	Dancing data mining	1144
	Classification of dancing data mining	497
Filter by years and article type.	Dancing data mining	318
	Classification of dancing data mining	171
Filter by years, article type and access type.	Dancing data mining	106
	Classification of dancing data mining	34

2.2 Classification techniques

There were various classification approaches attempted in existing works. Among the popularly focused areas were analyses using skeleton animations. For instance, investigation of real-time classification of dance gestures from skeleton animation by using the real-time depth sensor (Raptis et al., 2011). The authors applied the real-time techniques which include an angular representation of the skeleton designed under noisy input, a cascaded correlation-based classifier for multivariate time-series data, and a distance metric based on dynamic time warping to evaluate the difference in motions between gestures. As compared to accurate optical or mechanical marker-based motion capture systems, depth sensors offer better balance in usability and costs aspects. However, the consequence is the substantial increase in noise. It was also shown from the context of dancing, a classifier could be designed and trained to recognize dozens of gestures in real-time and with high accuracy (Raptis et al., 2011).

On the other hand, Heryadi et al. (2012) studied the syntactical modelling and classification for performance evaluation of Bali traditional dance. In Heryadi et al. (2012), a linguistically motivated approach for dance gesture performance was evaluated on skeleton tracking. The authors' findings showed that the most discriminative feature to represent dance gestures of Bali traditional dance were skeleton feature descriptor extracted from the performer's elbow and feet. The gesture model built in their study was able to evaluate performance of a dance gesture by measuring alignment level between the tested dance gesture and dance master's gesture.

According to Shinoda et al. (2012), the Nihon Buyo dance movements extracted feature values could be classified by schools of Nihon Buyo using the motion capture system. In Shinoda et al. (2012), the experimental setups require devices like optical motion capture system (Motion Analysis, MAC3D system) with 12 cameras, that enabled capturing at a frame rate of 60 frames per second. Reflective markers were placed on the dancer's body at 42 knot locations covering the entire body from the top of the head to heel of the feet. (Figure 2.1). The body's centre of gravity was calculated from the positions of 14 segments of the body (head, torso, upper-arms, forearms, hands, thighs, shanks, and feet). The visualization system developed in there was able to present body's center of gravity in 3D and show a comparison of the motion for multiple dancers.

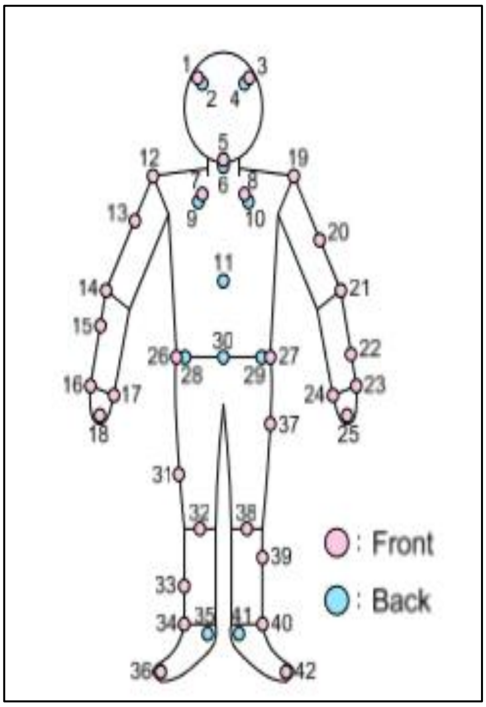

Figure 2.1: Position of reflective markers.(Shinoda et al., 2012).

The common Hidden Markov Models (HMM) approach was considered an effective and efficient for dance classification. Masurelle et al. (2013) investigated multimodal classification of dance movements by using body joint trajectories and step sounds. The authors presented a multimodal approach to recognize the isolated complex human body movements, namely Salsa dance steps. In Masurelle et al. (2013), multimodal dance gesture classification system took advantages of an original temporal-segmentation method of 3D body joint trajectories based on footstep impact detections so as to allow an efficient representation of motion features.

Kitsikidis et al. (2015) applied the unsupervised dance motion patterns classification from fused skeletal data by using the exemplar-based HMMs. The authors proposed a method for the partitioning of dance sequences into multiple motion patterns. They deployed features in the form of a skeletal representation of the dancers observed through time by using multiple depth sensors. Their proposed method was applied on a dance sequence of Greek traditional Tsamiko dance by using a setup of three depth sensors, which was placed around of the dancers as shown in Figure 2.2. This proposed method was seen to have excellent performance with low segmentation error percentage (0.27%). (Kitsikidis et al., 2015).

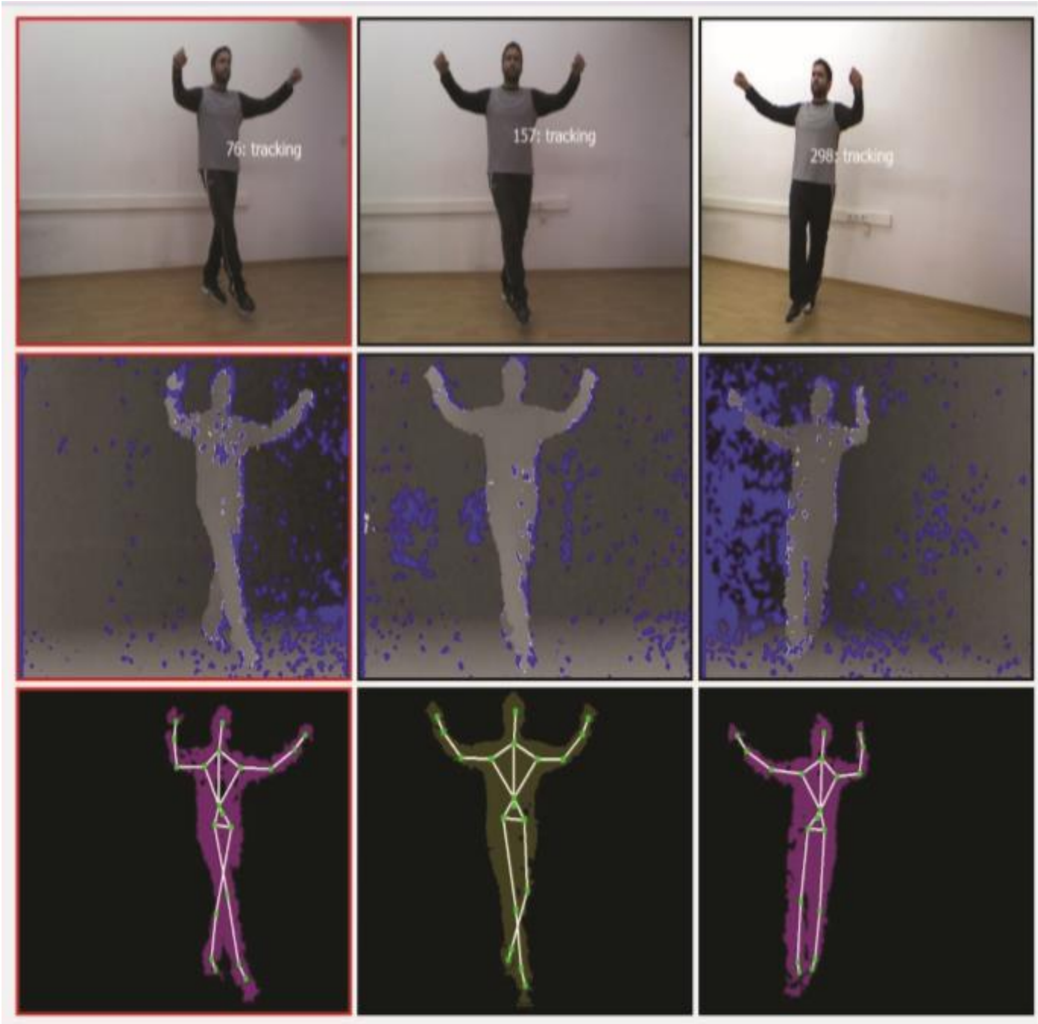

Figure 2.2: Motion capture with three Kinect sensors placed around the dancer.(Kitsikidis et al., 2015)

Samanta and Chanda (2014) classified the Indian classical dance on manifold by using Jensen-Bregman LogDet Divergence. In their study, data features were represented at each space-time interest point by fusing different order spatial and temporal derivatives. Classification analysis was applied by using popular non-linear SVM with $\chi 2$-kernel. Their algorithms also tested on human activity benchmark datasets such as KTH, and UCF50. The system was also evaluated on ICD dataset created from YouTube with the accuracy found higher than other human activity classification algorithms such as histogram of optical flow (HOF) and histogram of oriented gradient (HOG) (Samanta & Chanda, 2014).

Karavarsamis et al. (2016) classified Salsa dance steps from skeletal poses. Salsa dance step primitives were detected in choreographies available in the Huawei 3DLife data set. The dance steps adopted in their paper is a concatenation of vectorized matrices involving the 3D coordinates of tracked body joints. As compared to common classifiers like stochastic gradient descent and K-Nearest Neighbours**,** this model was able to produce more accurate results by computing a subspace of the data. Also, it can reduce biasness due to the uneven distribution of time step data across data classes (Karavarsamis et al., 2016).

Kim et al. (2017) also classified K-pop dance movements based on skeleton information on the skeletal joint data using a Kinect camera. The authors constructed a K-pop dance database with a total of 800 dance-movement data points including 200 dance types produced by four professional dancers (two men and two women) from skeletal joint data obtained by a Kinect sensor. They designed an efficient Rectified Linear Unit (ReLU) based Extreme Learning Machine Classifier (ELMC) with an input layer composed of these feature vectors transformed by fisherdance. In contrast to conventional neural networks, the presented classifier achieved a rapid processing time without implementing weight learning. The experimental results showed that the proposed Rectified Linear Unit (ReLU) based Extreme Learning Machine Classifier (ELMC) approach demonstrated a better performance in comparison to KNN (K-Nearest Neighbor), SVM (Support Vector Machine), and ELM alone (Kim et al., 2017).

Kumar et al. (2017), whereas, classified the Indian classical dance with Adaboost multiclass classifier on multifeatured fusion. In the authors' approach, the complicated problem of automatic human action recognition is addressed using unconstraint video sequence of Indian classical dance. The classifier was fed with five types of features calculated on Zernike moments, Hu moments, shape signature, local binary pattern (LBP) features, and Haar features. In order to improve the classification process, Kumar et al. (2017) explored multiple feature fusion models with the early and late fusion during and after video segmentation stage. The authors showed recognition on Indian classical dance videos from both offline (controlled recording) and online (Live Performances, YouTube) data (Figure 2.3). Their findings showed Adaboost classifier gave better classification accuracy if compared to adaptive graph matching (AGM) and support vector machine (SVM).

(a)

(b)

Figure 2.3: Online Indian classical dance data sets from YouTube (a) Offline dance video data set in a controlled lab environment (b) (Kumar et al., 2017)

Kumar and Kishore (2017) applied HOG features and SVM classifier to classify Indian classical dance. In their work, classical dance mudras in various dance form in India were explored and recognized. The classifier was input by histogram of oriented (HOG) features of hand mudra (a symbolic or ritual gesture) while the support vector machine classifies the HOG features into mudras as text messages. In Kumar and Kishore (2017), the learning capacity for the first-time learner can be enhanced with the help of mudra classification model.

Kishore et al. (2018) identified and classified Indian classical dance action with convolutional neural network (CNN). The authors also showed recognition on Indian classical dance videos from both offline (controlled recording) and online (Live Performances, YouTube) data. CNN training is performed with eight different sample sizes while the remaining two samples were used for testing the trained. CNN model achieved high average recognition rate; 93.33% and higher compared to other state-of-the-art classifiers like histogram of oriented (HOG) features and support vector machine (SVM) (Kishore et al., 2018).

Existing dance classification analysis show many emphases on Hidden Markov Models (HMM) algorithms apart from using other algorithms such as support vector machine (SVM), hierarchical cluster analysis, histogram of oriented (HOG) features, convolutional neural network (CNN) and Adaboost multiclass classifier. In addition, most of the studies use offline real time dance video which setup in a controlled lab environment instead of using available online dance video from publicly source. Only three papers use both offline and online dance videos for data collection purpose. The motion capture system used by dance study researchers for skeleton tracking consists of MAC 3D system, Microsoft Kinect II sensor and X-BOX Kinect sensor.

2.3 Pattern recognition

Dance pattern recognition and classification were sometimes used interchangeably. The difference between pattern recognition and classification is that pattern recognition involves the process of recognizing regularities or patterns in data by using machine learning algorithm while classification is an example of pattern recognition which use model to divide the data into categories according to their type.

Saha et al. (2013) recognised gestures and distinguish between 'Anger', 'Fear', 'Happiness', 'Sadness' and 'Relaxation' emotions from Indian classical dance by using the Kinect Sensor. Kinect sensor generates the skeleton of human body from eleven coordinates. A unique system of feature extraction was used and a model for gesture classification was developed in their study (Figure 2.4). A total of twenty-three features were extracted based on the distance between different parts of the upper human body, the velocity and acceleration generated along with the angle between different joints. The recognition rate for this proposed algorithm is high with 86.8% by using Support Vector Machine (SVM) (Saha et al., 2013).

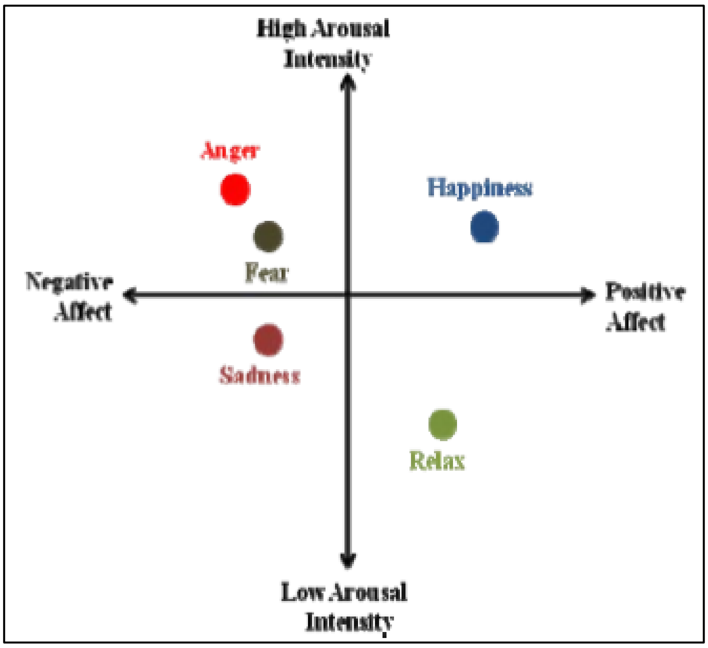

Figure 2.4: Model for gesture classification (Saha et al., 2013).

In a different study, Saha et al. (2013) applied the fuzzy image matching method to recognise postures in Ballet dance. The authors aimed to design a fuzzy matching algorithm that can automatically recognize an unknown ballet posture from seventeen fundamental ballet dance primitives. Findings from Saha et al. (2013) showed 84.6% accuracy independent of the body type, height and weight of the ballet dancers. However, the performance of the algorithm will drop in the case when the postures were found almost identical, thus the proposed algorithm fails to differentiate in some cases (Saha et al., 2013).

Anbarsanti and Prihatmanto (2014) studied the dance modelling, learning and recognition system of Aceh traditional dance based on hidden Markov model. For the robustness under noisy input of Kinect sensor, an angular representation of the skeleton was designed, and a pose of dance was defined by the angular skeleton representation, quantified based on the range of movement. One unique gesture of dance was defined by sequence of pose and learned and classified by HMM model (Anbarsanti & Prihatmanto, 2014).

Besides, Saha and Konar (2015) used topomorphological approach to recognise the automatic posture in ballet dance. Automatic posture referred to automatic identification of an unknown dance posture. In this proposed system, an unknown dance posture was automatically identified by referring to 20 primitive postures of ballet. The group of an unknown posture is determined based on its Euler number. This proposed system showed a high overall accuracy of 91.35% for recognising unknown postures (Saha & Konar, 2015).

Protopapadakis et al. (2017), whereas, investigated the folk-dance pattern recognition on depth images acquired via the Kinect sensor. The identification abilities of classifiers over folk dance were conducted while the impact of the body joint regions was also identified. The system inputs were only raw skeleton data, which provided by a low-cost sensor while the data were obtained by monitoring three professional dancers using the Kinect II sensor. The most descriptive skeleton data were selected using a combination of density based and sparse modelling algorithms. Then, the representative data was served as training set for a variety of classifiers (Protopapadakis et al., 2017).

In dance recognition, many researchers used the Kinect device in order to capture the dance motion for the dancers. Of all algorithms used, HMM model was considered an effective and efficient method of both learning and classifying dance gestures involving several joints. Also, other approaches such as fuzzy image matching method and topomorphological approach were used for pattern recognition in dances.

2.4 Dance Motion Analysis

The dance motions are also analysed from the perspectives of classify and recognise the dances. Miura et al. (2010) extracted the motion analysis in dances by statistical analysis of joint motions. The authors select the variance-covariance matrix (Figure 2.5) given by the statistical analysis of joint motion's time-series data to characterize dance motions. The application of multidimensional scaling (MDS) was effective to extract the distribution feature of a dance database. The advantage of this study is the comparison of multiple dances becomes easy, This is due to the integrated representation form is unaffected by the variation of motion data (Miura et al., 2010).

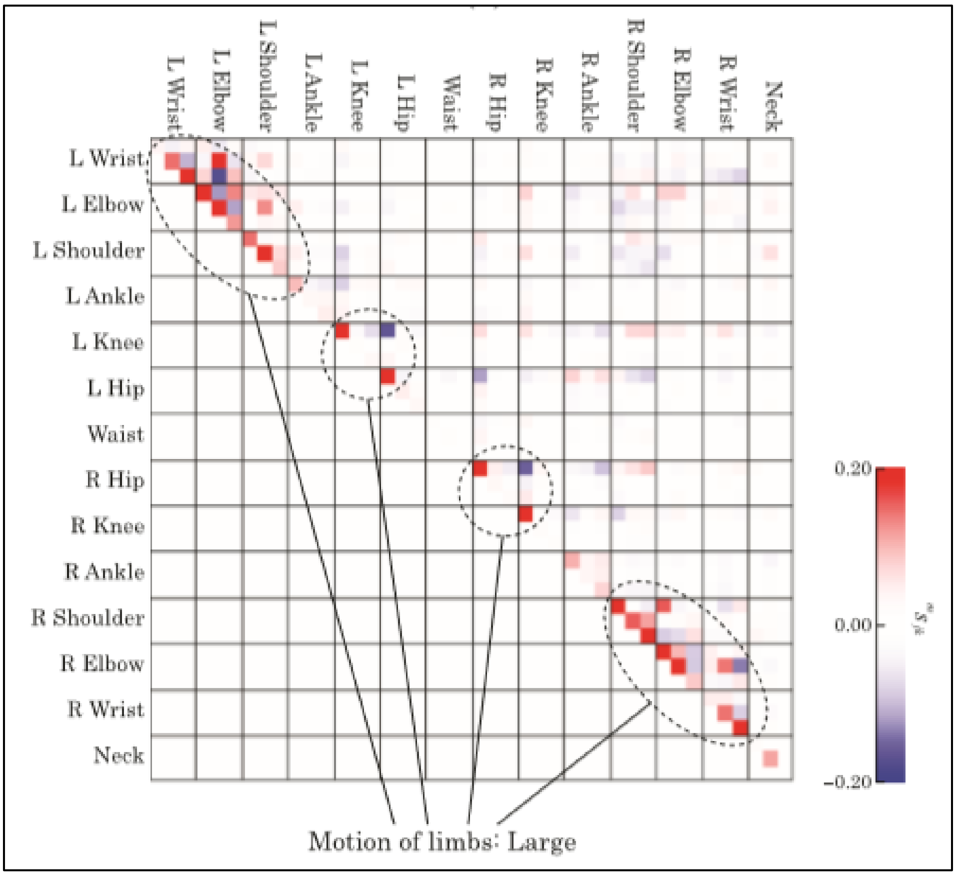

Figure 2.5: Variance-covariance matrix (Miura et al., 2010).

Some researchers applied the motion capture system in order to analyse dance motions.(Shinoda et al., 2012). A motion capture system is usually built to visualize the body motion and the centre of gravity of dancers. For instance, Yamane and Shakunaga (2010) analysed the dance motion by correlation matrix between pose sequences. The dance motion analysis was discussed based on correlation matrices calculated between two motion sequences captured by a motion capture system with multiple camera

(Figure 2.6). The authors showed that similar motion segments between two motions result in diagonal region on the correlation matrix (Yamane & Shakunaga, 2010).

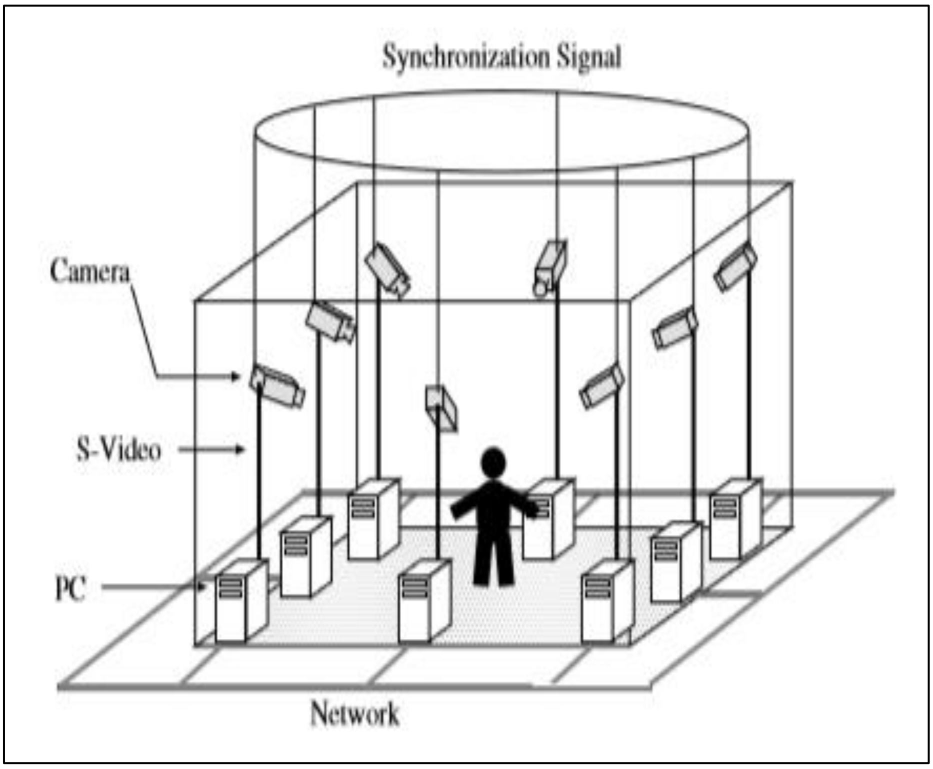

Figure 2.6: Motion capture system with multiple camera (Yamane & Shakunaga, 2010).

On the other hand, Miura (2013) analysed the Japanese folk dance “Hitoichi Bon Odori” motion quantitatively. An investigation on the motion characteristics of Hitoichi Bon Odori was present in this study. It was shown that the expanse in rhythmic style and posture variation for Hitoichi Bon Odori dance is very large. The motion characteristics peculiar to Hitoichi Bon Odori were quantitatively clarified based on motion capture data analysis (Miura, 2013).

Aristidou et al. (2014) applied motion analysis for folk dance evaluation. In this paper, a motion analysis and comparison framework based on Laban Movement Analysis (LMA) was introduced. This system provides intuitive feedback about the performance based on four LMA components which are body, effort, shape and space. Also, provides both quantitative and qualitative evaluation for performance. In this work, a novel motion comparison algorithm is built. It compares the movements of two avatars not only by the posture matching (physical geometry of the avatar) but also the style, including the required effort, shape, and interaction of the performer with the environment (Aristidou et al., 2014).

2.5 Summarization for Related Studies

The related studies from dance researchers applied difference research approaches, algorithms and skeleton tracking method. Besides, they also used different raw video sources. The summarization for the studies is displayed as shown in fishbone diagram (Figure 2.7).

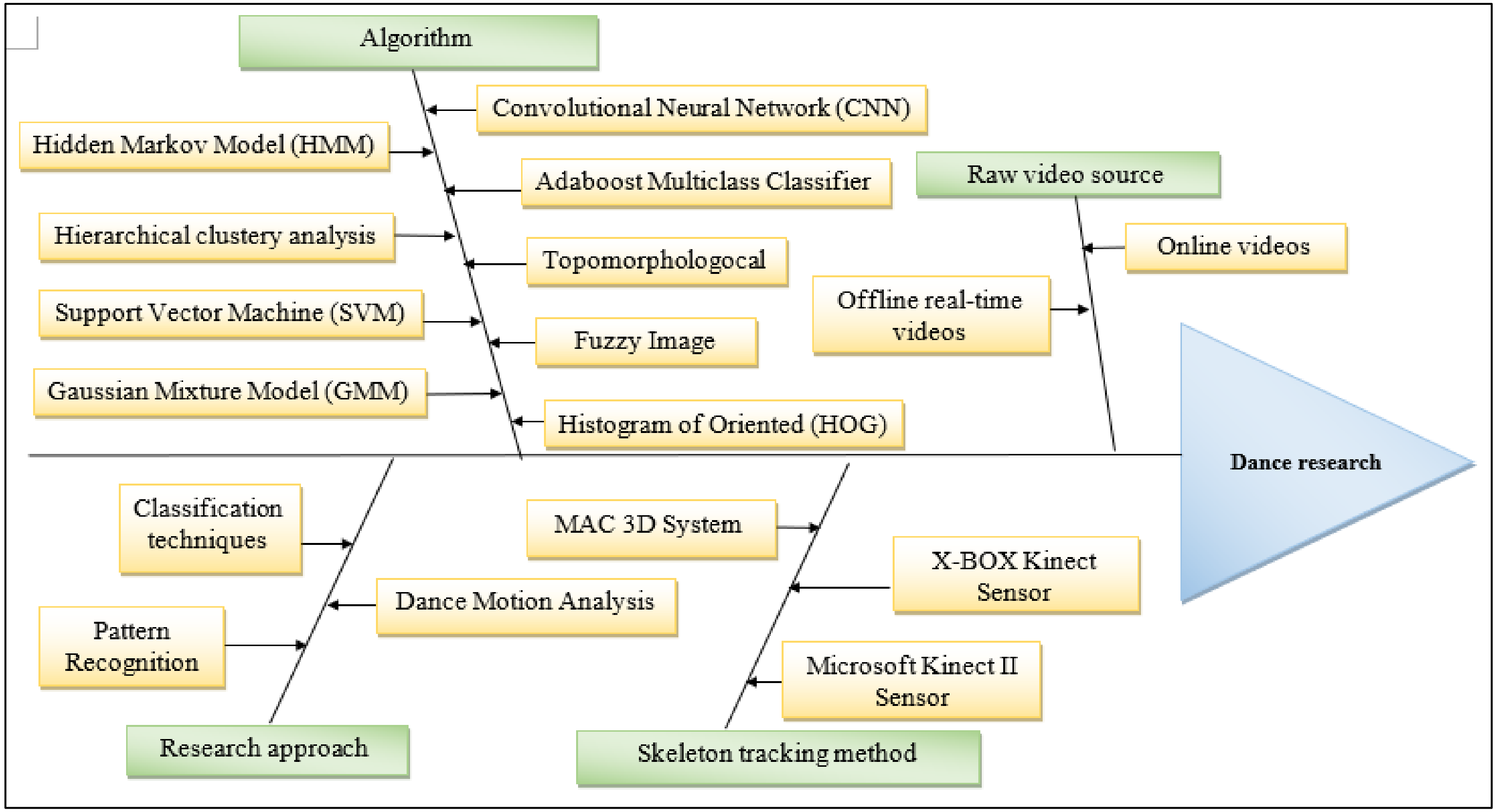

Figure 2.7: Fishbone diagram of dance research.

2.6 Challenges and Issues

Overall literature works varied by methods that are useful to classify the dance gestures and the motion patterns. Approaches adopted in existing studies were classification, pattern recognition and dance motion analysis. Classification studies were performed using Hidden Markov Model (HMM), support vector machine (SVM), hierarchical cluster analysis, histogram of oriented (HOG) features, convolutional neural network (CNN) and Adaboost multiclass classifier and many other algorithms. While these studies are important for dance classification, the lacking was that no works have attempted the data mining approach to examine the speed, coordinates and motion posture pattern variations to distinguish type of dances.

Kinect device were commonly used in skeleton tracking. Others used motion capture system such as multiple-camera system. Another potential application is using Kinovea. The strength for Kinovea is that it is a free and open source. Also, it is a simple and user-friendly software. However, there are limitations in the sense that it requires manual effort to track the body joints by using marker.

CHAPTER 3

RESEARCH METHODOLOGY

3.0 Overview

This chapter presents the approaches to classify the Indian classical dances into five classes which includes Kathak, Bharatanatyam, Kuchipudi, Manipuri and Kathak based on motion posture patterns. In general, the entire research implementation was divided into four main stages, which includes Data Collection, Data pre-processing, Data Classification and Knowledge Discovery as shown in Figure 3.1. Initially, the markerless video sources were extracted from publicly available domain to undergo joint tracking processes in Kinovea software. The attributes extracted from the raw data were tabulated along with the corresponding instances. Data mining approach begins with data pre-processing analysis using Weka software in order to remove the outliers and extreme values so that the data is clean and has higher quality. This was followed by the classification analysis on the raw and pre-processed data. The percentage of classification accuracies between the raw and pre-processed data were compared. At knowledge discovery level, significant attribute analysis was performed using three approaches: (i) removal of single attributes, (ii) removing attributes by category and (iii) removal of attributes by joint. Classification error analysis was performed at the final stage for this level.

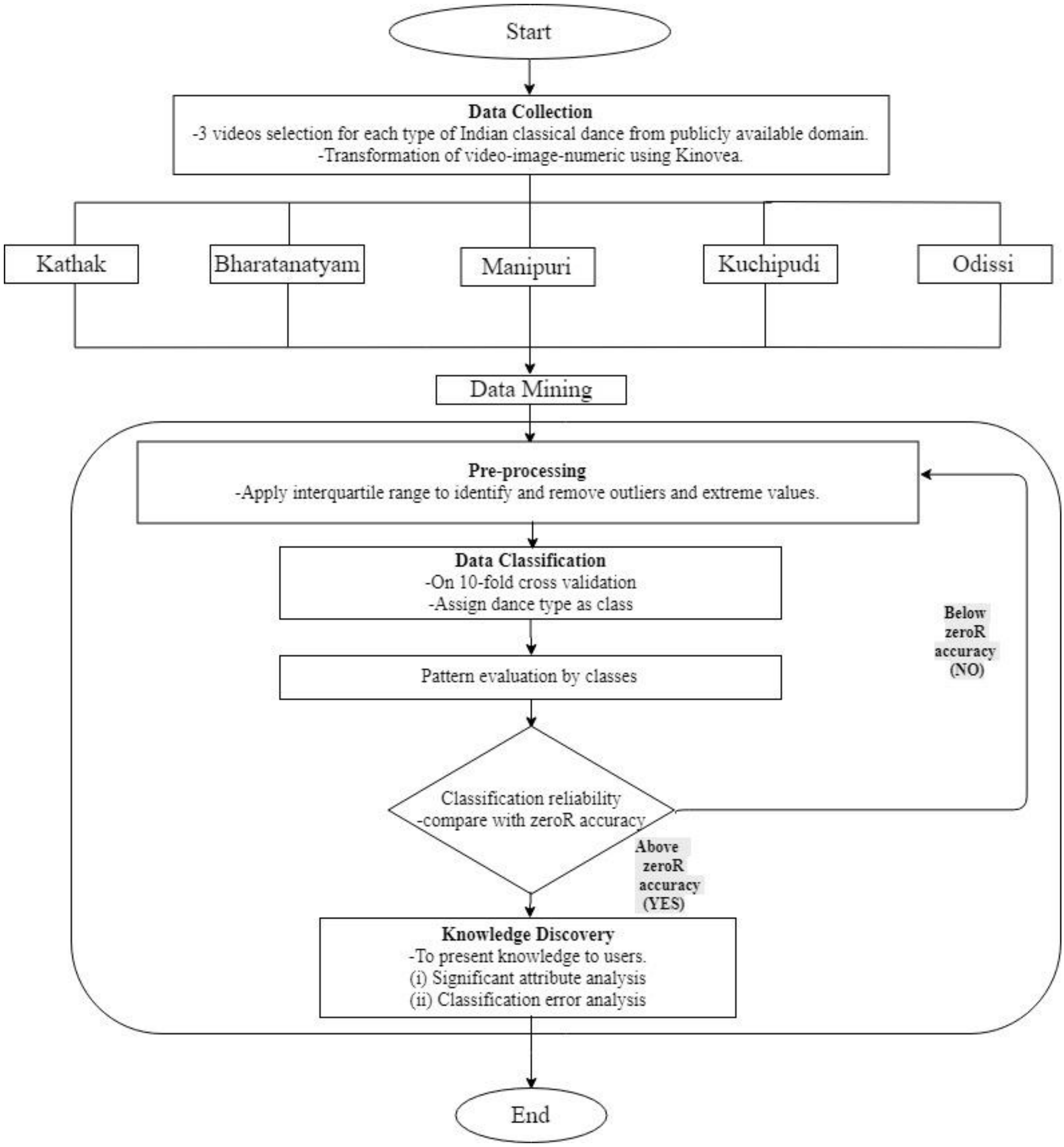

Figure 3.1: Flowchart of data mining approach for classifying the Indian classical dances.

3.1 Data Collection

There were five types of Indian classical dances retrieved from three markerless video sources for each type which include Kathak, Bharatanatyam, Kuchipudi, Manipuri and Odissi.

- Kathak (“Meghranjani - Sudha Nritya (kathak Dance) - YouTube,” n.d.), (“Kathak Dance | Vidya Patel | TEDxBrum - YouTube,” n.d.), (“Yuvraaj Parashar Kathak Dance - YouTube,” n.d.).
- Bharatanatyam (“RAMAVATARA KOUTHUVAM by Harinie Jeevitha - Sridevi Nrithyalaya - Bharathanatyam Dance - YouTube,” n.d.), (“Chanda Tala Alarippu by Harinie Jeevitha - Sridevi Nrithyalaya - Bharathanatyam Dance - YouTube,” n.d.), (“Bho Shambho - Bharatanatyam solo performance by Surabhi Bharadwaj - YouTube,” n.d.).
- Kuchipudi (“Kuchipudi Dance on Guru by Lasya Mavillapalli - YouTube,” n.d.), (“Kuchipudi Dance by Manju Bharggavee - Part 3 | Marakatha Manimaya Chela | Indian Classical Dance - YouTube,” n.d.), (“Krishna Shabdam: Kuchipudi by Sandhya Raju - YouTube,” n.d.).
- Manipuri (“MANIPURI DANCE-KRISHNA NARTAN-PART 1 BY KONSAM SUJATA DEVI - YouTube,” n.d.), (“Manipuri dance by Bimbavati Devi Part 2, Invis Multimedia Nani Churi DVD - YouTube,” n.d.), (“Manipuri Nani Churi_by Hemant Viswakarma - YouTube,” n.d.).
- Odissi (“Maryam Shakiba - Odissi Dance - Manglacharan Ganesh Vandana - YouTube,” n.d.), (“‘Odissi Mangalacharan’ - Sujata Mohapatra (Part 1 DVD) - YouTube,” n.d.), (“Odissi - Mangalacharan ——Ganesha Vandana - YouTube," n.d.).

There were total of 15 subjects, all of them are professional dancer which consists of 13 females and 2 males. However, the gender of dancers was not considered as the attribute for this study. The images for all videos are shown in Appendix 1.

3.2 Data Transformation

The video files were imported into Kinovea software in order to transform into image and numeric data for further analysis. Figure 3.2 shows the user interface for Kinovea after the video was imported. The transformation from video to image was performed by using "Track Path" function in Kinovea. Frames per second (fps) at capture time for every video data was according to the default system of Kinovea and it was set at 25fps (0.04s). 25fps is sufficient for this study since it is a sampling rate adequate for locating dancers moving around in most dances. Fps is a unit that measures camera performance where it determines how many unique consecutive images a camera can handle per second (equation (3.1)). In other words, there are 25 images transformed for every second.

$$Frame\ per\ second\ (fps) = \frac{1}{time\ frame\ (s)} \tag{3.1}$$

The images were markerless and therefore a predefined five main body joints: forehead, right wrist, left wrist, right ankle and left ankle were marked for the subjects and traced by using markers in Kinovea software as shown in Figure 3.3. The images of motion tracking are shown in Appendix 2. The reference origin was set at coordinate (0,0). The joint coordinates will be used to evaluate the motion speed frame to frame.

After the motion-tracked images were obtained, image-numeric transformation process was carried out. This was carried out through exporting the images data in Kinovea to worksheet in Microsoft Excel. The study attributes extracted from the video files included body joint coordinates, time frame, and its derived quantities-motion speed of joints. In order to calculate the speed of joints, distance formula was applied. This formula was performed by dividing the distance of joints with time frame (equation (3.2)) where the distance of joints from x and y-coordinates were calculated based on the Pythagorean Theorem calculation (equation (3.3)).

$$Speed\ of\ joints\ (ms^{-1}) = \frac{Distance\ of\ joints}{Time\ frame} \tag{3.2}$$

$$Distance\ of\ joints\ (m) = \sqrt{(dx)^2 + (dy)^2} \tag{3.3}$$

where

$dx = x_2 - x_1$

$dy = y_2 - y_1$

The five types of dances were defined as nominal class attribute. The recorded data in Microsoft Excel Worksheet were transformed into Microsoft Excel CSV File format readable by Weka Explorer for data pre-processing, data classification and significant attribute analysis.

Figure 3.2: User interface for Kinovea after the video is imported.