2D HUMAN MOTION ESTIMATION MODELING FOR CLASSIFICATION

by

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LIST OF ABBREVIATIONS

2D	2-Dimensional
3D	3-Dimensional
ANN	Artificial Neural Network
ANOVA	Analysis of Variance
AVE-SAT	Actual time step Value Estimate with Segregated Average Tolerance
AVE-TAT	Actual time step Value Estimate with Total Average Tolerance
BAPs	Body Animation Parameters
BB	Backbone
BDPs	Body Definition Parameters
C	Child's pose
CCR	Correct Classification Rate
CM	Camel pose
CMU	Carnegie Mellon University
DBN	Dynamic Bayesian Network
DT	Decision Tree
DTW	Dynamic Time Warping
GA	Genetic Algorithm
GIGO	Garbage In, Garbage Out
HCI	Human Computer Interface
HD	High Definition
HDM	Hochschule der Medien
HMM	Hidden Markov Model
IBk	Instance Based Learner

IVE-SAT	Initial Value Estimate with Segregate Average Tolerance
IXMAS	INRIA Xmas Motion Acquisition Sequences
J1	Jumping_1
J2	Jumping_2
KGGM	Kinematic Gait Generative Model
k-NN	*k*-Nearest Neighbors
KTH	Kungliga Tekniska Högskolan
L	Leg lock pose
LB	Lower Body
LMT	Logistic Model Trees
LWL	Locally Weighted Learning
MB	Marker-Based
MCMC	Monte Carlo Markov Chain
ML	Marker-Less
MoCap	Motion Capture
MTRNN	Multiple Timescale Recurrent Neural Network
N	No
NN	Neural Network
P	Punching
PCA	Principle Component Analysis
PIR	Pyroelectric Infrared
R1	Running_1
R2	Running_2
RBF	Radial Basis Function

SMO	Sequential Minimal Optimization
SP	Sword playing
STES	Spatio-Temporal Energy Sequence
SVM	Support Vector Machine
T	*Taichi*
UB	Upper Body
UCF	University of Central Florida
VGGM	Visual Gait Generative Model
W1	Walking_1
W2	Walking_2
WEKA	Waikato Environment for Knowledge Analysis
Y	Yes

LIST OF SYMBOLS

b_n	Coefficients values
Δb_n	Deviation of coefficient
$\overline{\Delta b}$	Average deviation of coefficient
$b_{n_{t_{n+1}}}$	Coefficient value of i^n at time step of t_{n+1}
$b_{n_{t_n}}$	Coefficient of i^n at time step of t_n
B_x	Back bone (*x*-coordinate)
B_y	Back bone (*y*-coordinate)
d	Last time step of motion data
H	Hypothesis of $\boldsymbol{X}$ being group into its specific motion class
i	Predefined body joints values
I	2D stick model
I_{t+1}	Estimated stick model at $t + 1$
k	Predefined polynomial order
L_x	Lower body (*x*-coordinate)
L_y	Lower body (*y*-coordinate)
M_{PCA_i}	Motion sequence of the subject in PCA space
M_{PCA_j}	Sample motion sequence in PCA space
$P(\boldsymbol{X})$	Probability of $\boldsymbol{X}$ group into its specific motion class
$P(\boldsymbol{X}\vert H)$	Probability of $\boldsymbol{X}$ that categorized into specific classes with the condition on hypothesis H
R^2	Coefficient of determination
S	Segment model

t	Motion time steps
U_x	Upper body (*x*-coordinate)
U_y	Upper body (*y*-coordinate)
x	Predictor
$\boldsymbol{X}$	Motion data
y	Respondent
$\bar{\varepsilon}_{\mathrm{S}}$	Segment tolerance model
$\%\ Y$	Matching accuracy

PERMODELAN ANGGARAN 2D PERGERAKAN MANUSIA UNTUK PENGELASAN

ABSTRAK

Penganggaran pergerakan manusia ialah pendekatan untuk menganggarkan aktiviti pergerakan daripada postur badan statik; diterokai secara meluas melalui pergerakan gaya berjalan, analisis berasaskan bayang, berasaskan biomekanik atau berasaskan imej untuk tujuan rakaman pergerakan, pengecaman, dan pengawasan melalui pemerhatian. Pergerakan manusia selalunya dirakamkan melalui sistem *Berasaskan-Penanda* (BP) dan *Tanpa-Penanda* (TP) dengan sebuah atau beberapa buah kamera. Pergerakan-pergerakan ini biasanya dianalisis dalam posisi 3-Dimensi (3D) atau 2-Dimensi (2D) dengan melibatkan lokasi dan orientasi sendi-sendi tubuh. Walau bagaimanapun, disebabkan kerumitan data pergerakan berdimensi tinggi, kajian ini memfokuskan pergerakan 2D manusia. Model kayu 2D yang telah dibangunkan kurang berkeupayaan untuk mengenal pasti lokasi sendi tubuh. Selain itu, tiada penyelidik yang pernah mempertimbangkan pelarasan toleransi dalam penganggaran pergerakan manusia. Oleh itu, tujuan utama kajian ini ialah membangunkan sebuah model penganggaran kayu 2D dengan toleransi ralat untuk mewakili pergerakan manusia untuk analisis pengelasan. Model penganggaran kayu 2D dibangunkan daripada tiga segmen asas tubuh: *Tulang Belakang* (TB), *Atas Tubuh* (AT) dan *Bawah Tubuh* (BT). Dengan pertimbangan keupayaan regangan segmen-segmen tubuh ketika melakukan aktiviti yang berbeza, model toleransi dihasilkan daripada purata bezaan pekali penyesuaian polinomial yang dihitung pada jujukan langkah masa. Mengintegrasikan koordinat langkah masa yang sedia ada dengan model toleransi ini secara berulang-ulang menghasilkan anggaran koordinat sendi tubuh pada jujukan langkah masa yang seterusnya. Model yang dibangunkan ini diuji pada (i) pergerakan asas BP: berjalan, berlari, melompat; dan pergerakan sukan BP: menumbuk, bermain pedang dan *taichi* daripada pangkalan data CMU; dan (ii) pergerakan asas TP: berjalan, berlari, melompat daripada YouTube; dan pergerakan sukan TP: pergerakan Yoga kanak-kanak, kunci kaki dan gaya unta secara rakaman eksperimen. Transformasi data dimulakan dengan pengambilan gambar data video kepada imej pegun diikuti oleh transformasi imej kepada data koordinat. Penghapusan data bersama imputasi regresi dijalankan untuk membaik pulih data yang hilang akibat oklusi dan segmen tubuh yang tersembunyi. Model penganggaran pergerakan untuk pertimbangan toleransi ini dilaksanakan dengan tiga kaedah penganggaran pergerakan 2D: IVE-SAT, AVE-SAT dan AVE-TAT. Model penganggaran kayu 2D ini dinilai atas analisis padanan dan ketepatan pengelasan dengan menggunakan pengelas *Lazy*. Dapatan kajian menunjukkan bahawa model penganggaran kayu 2D dengan AVE-TAT ini menghasilkan ketepatan padanan sehingga 66.67% dan ketepatan pengelasan melebihi 90% bagi semua kategori pergerakan. Model yang dibangunkan ini mempunyai kelebihan atas keupayaannya untuk menganggarkan pergerakan manusia secara spesifik dengan pelarasan toleransi ralat yang menyerupai regangan segmen tubuh sepanjang keseluruhan aktiviti. Hasil kajian ini berjaya membuktikan bahawa model penganggaran kayu 2D dengan AVE-TAT yang dicadangkan ini ialah pendekatan yang boleh dilaksanakan untuk membezakan ciri-ciri pelbagai pergerakan manusia untuk pengelasan.

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2D HUMAN MOTION ESTIMATION MODELING FOR CLASSIFICATION

ABSTRACT

Human motion estimation is an approach to predict motion activities from static body postures; widely explored from gait motion, silhouette-based, biomechanical-based or image-based analyses for motion capture, recognition and vision surveillance purposes. Human motion is often captured via Marker-Based (MB) and Marker-Less (ML) system by using single or multiple cameras. These motions are commonly analyzed in 3-Dimensional (3D) or 2-Dimensional (2D) positioning involving location and orientations of body joints. Nevertheless, owing to the complexity of high dimensionality motion data, this study has focused on the 2D human motion. Existing developed 2D stick figures could hardly point the exact body joint location. Besides, no researchers have considered the tolerance adjustment for human motion estimation. Therefore, the main goal of this study is to develop a 2D stick estimation model with error tolerance to represent human motions for classification analysis. The 2D stick estimation model is developed from three fundamental body segments: Backbone (BB), Upper Body (UB) and Lower Body (LB). Considering the capability of body segments' stretches while performing different activities, tolerance model is derived from the average deviations of polynomial fitting coefficients evaluated at sequential time steps. Integrating the precedent time-step coordinates with the tolerance model iteratively yield the estimated body joint coordinates at subsequent time step. The developed model is tested on (i) MB basic motions: walking, running, jumping and MB sports motions: punching, sword playing and *taichi* from CMU database and (ii) ML basic motions:

walking, running, jumping from YouTube and ML sports motions: Yoga motion of child's, leg lock and camel pose from experimental captures. Data transformation is initiated to snapshot the video data into still images followed by image transformations into coordinate data. Data elimination cum regression imputation is carried out to treat missing data found from occlusion and hidden body segments. The motion estimation model for tolerance consideration is performed on three 2D motion estimation techniques: IVE-SAT, AVE-SAT and AVE-TAT. The 2D stick estimation model is judged on matching analysis and classification accuracies using Lazy classifiers. Findings show that the developed 2D stick estimation model by AVE-TAT resulted in best matching accuracy up to 66.67% and classification accuracies above 90% for all motion categories. The developed model has the advantage over its ability to estimate human motions specifically with error tolerance adjustment resembling the body segment stretches throughout the entire activity. The study outcomes successfully imply that the proposed 2D stick estimation model with AVE-TAT is a feasible approach in distinguishing characteristics of different human motions for classifications.

CHAPTER 1

INTRODUCTION

1.0 Overview

This chapter introduces the background of human motion and classification analysis in this study. The common issues and problems faced by previous researchers that motivate the study are also discussed. The objectives of this study are presented in section 1.4. This is followed by the scope of study with main focus on the human motion estimation and classification works as detailed in section 1.5 and the overall thesis outline in section 1.6.

1.1 Study background

Human motion concerns the movement of body segment to form motion activity. Human motion analysis is generally carried out to understand or recognize the human behavior from these bodily movements. The human motion analysis has been an active research in areas of computer vision and artificial intelligence with major applications in surveillance, information retrieval and criminal identification. In computer vision, the study interests mainly fall under the area of human motion capture in surveillance system. For example, surveillance system of the parking lot is used to identify the criminal behaviors under surveillance. Meanwhile, in artificial intelligence area, applications involve the animation, gaming and robotic motion such as in Castellano et al. (2013) study where the robotic game partner reacted based on the expression of a player during the gaming interaction. Human motion analysis is popularly understood from the science of human behaviors through the raw motion data obtained either by the public domain or self-captured motion video.

As different behaviors or motion patterns are observed from the captured motions, the motion pattern recognition is often a popular research field (Moeslund & Granum, 2001). The raw motion data or the motion capture could be recorded in 2-dimensional (2D) or 3-dimensional (3D) format depending on the field of interests. The 2D motion analysis is much easier task as compared to 3D analysis as the complex combination of 2D information is required to generate collective 3D motion representation (Moeslund & Granum, 2001). In order words, additional works are required to collect the third dimension data.

The initial stage of human motion analysis normally begins with the raw motion data collection. Two approaches are frequently used; Marker-Based (MB) or Marker-Less (ML) capturing approach. The distinct feature between the two approaches is the body marker. Body marker refers to sensors attach on body joints according to the anatomical topology of human i.e. bones, muscles and joints of the human body (Xiao et al., 2008). The marker is often treated as a sensor to transmit the location of the body joint. Commonly, the linkage of all the markers will represent human motion. MB capturing is the method that uses body markers attached on the body joints' positions based on anatomical topology. The markers attached on the subject are required to be matched tightly on the body surface in order to record an accurate location of body joint. As it is not convenient to attach markers on naked body surface, MB capturing method is usually performed on the subject with specific tight attire (a jumpsuit) which could minimize the gap between the marker and body surface. The markers attached on the body joints need to be visible from the camera to avoid occlusion conditions. Meanwhile, ML is a motion capturing method without considering any marker attachment on the subject. As mentioned by Mündermann et al. (2006a), ML can be categorized into two different categories namely the active and passive vision system. Active systems emit light information in visible or infrared light spectrum in the form of laser light, light patterns or modulated light pulses on the subject. This is in order for the subject to receive information of human motion. Meanwhile, a passive system is merely used on captured images. ML differs from MB capture method in the sense that the calibration time and costs of the apparatus or equipment used is relatively inexpensive as compared to MB capture method (Poppe, 2007). The common publicly available motion database adopted in the state-of-the-art reviews since year 2003 include the Carnegie Mellon University (CMU) (CMU, 2003), Kungliga Tekniska Högskolan (KTH) (Schuldt et al., 2004), INRIA Xmas Motion Acquisition Sequences (IXMAS) (Weinland et al., 2006), Weizmann (Gorelick et al., 2007), University of Central Florida (UCF) sports (Rodriguez et al., 2008) and HumanEva (Sigal et al., 2010) motion capture (MoCap) databases. The CMU database is a MB capturing method where markers are attached on the subject during the capturing process. On the other hand, KTH, IXMAS, Weizmann, UCF-sports and HumanEva database is a ML capturing method using single (KTH, Weizmann and UCF-sports) or multiple cameras (IXMAS and HumanEva) in capturing the subject. While KTH, Weizmann and UCF-sports database merely require single camera in capturing the subject; in which it is often applied in 2D motion analysis. On the other hand, CMU, IXMAS and HumanEva database can be used in either 2D or 3D motion analysis.

As raw human motion data retrieved is not easily understood, such situation has eventually led to a more comprehensive human motion analyses with the data mining techniques. Data mining is a process to analyze data from different