Journal of Engineering Science and Technology
Vol. 13, No. 7 (2018) 1967 - 1978

IMPACT OF NUMBER OF ATTRIBUTES ON THE ACCURACY OF HUMAN MOTION CLASSIFICATION

CHOON K. CHAN*, GIRMA T. CHALA

Mechanical Engineering Department, Faculty of Engineering and Quantity Surveying,
INTI International University, Persiaran Perdana BBN,
Putra Nilai, 71800 Nilai, Negeri Sembilan, Malaysia
*Corresponding Author: choonkit.chan@newinti.edu.my

Abstract

The quality of the human motion data faces challenges in producing high classification accuracy in large data streams for essential knowledge discovery. This reflects the need to identify the key factors that affect the results of classification. Present studies merely focus on estimating joints, skeleton and motions of human activities. However, the effect of the number of attributes towards classification accuracies of human motion has not been discussed. Therefore, this paper is aimed at determining the amount of attributes that affect the qualities of human motion classification. The case studies involve simple locomotion activities: jumping, walking and running retrieved from the public available domain. The raw video data were transformed into numeric in the form of *x* and *y*-coordinates and rotation angles as to be tested from a single up to triple combinations of data attributes. The impact of the number of attributes on classification accuracy is evaluated via Bayes, Function, Lazy, Meta, Rule and Trees classifier algorithms supported by the WEKA tool. Results revealed that three attributes data gave the best classification performance with an average accuracy of 81.50%. The findings also revealed that the number of attribute is directly proportional to the classification accuracy of human motion data.

Keywords: Attributes, Classification, Human motion, WEKA.

1. Introduction

Human motion analysis has been studied under various topics of interests in computer vision, image processing and machine vision involving different types of considerable attributes that mark the human body segments. The commonly discussed segments were the joints [1], skeleton [2, 3], and motion parameter estimation [4, 5].

Efforts have been made to relate these parameters for knowledge and information retrieval. These included estimation of joint parameters focusing on human body segment from the monocular image by Tong et al. [1] followed by deterministic nonlinear constraint optimization method using MATLAB and global location parameters of the human pose. These studies have also diverted the interests of other researchers such as Cameron and Lasenby [2] into body skeleton estimation and configuration technique based on marker optical motion capture where Liu et al. [3] had proposed to enhance skeleton visualization view by utilizing spatio-temporal data. To bring about a thorough estimation, the human skeleton rotation angle is also measured using Procrustes solver based on real markers. Apart from the joint and skeleton parameters estimation, other researchers have proposed the idea of dimensional motion parameter approximations. For instance, Cao et al. [4] focused on 3-Dimensional (3D) motion parameters estimation and object's centre of rotation based on a motion model; Eichner et al. [6] have researched on a 2-Dimensional (2D) articulated human pose estimation. Meanwhile, recent researchers had proposed to represent human motion by different approach including pixel information as the action representative for estimation [7], region-based mixture models that use motion trajectories for human action recognition [8] and sequential Kinect skeleton data for motion recognition [9].

Previous scholars' works indicated that human motion data analysis mainly focused on biomarker estimations from body segment joint markers, skeleton, motion parameters and pixel information [10]. This means that there is no clear cut on the investigation of the impact of key attributes on the data processing stage. Besides, the fusion of human joints and body segment rotation angles at a pre-processing level has not been discussed in detail by previous researchers. This paper was, therefore, designed to study the impact of attributes on classification accuracy. It is also the intention of our study to verify the impacts of the number of attributes on different types of simple human motion such as walking, running and jumping. Three main attributes were recorded: *x*-coordinate, *y*-coordinate and rotation angle at different time steps. At the end of this paper, the credibility of the combined attributes is judged from classification accuracies aspects using the Bayes, Function, Lazy, Meta, Rule and Trees methods.

2. Methodology

In this paper, the stability of the classifier in WEKA is tested on public available motion data. The process started with raw data collection, pre-processing, classification by WEKA and comparison of classification accuracy. The details of the research are explained in the subsection below.

2.1. Raw data collection

Raw motion data was collected from public video sources available from YouTube video sharing domain [11-13]. The activities involved simple movements involving jumping, walking and running performed by a single participant for a duration of 1 to 5 minutes. The jumping motions were performed on eight different skills for basketball training, while the walking and running motions were on a single skill.

2.2. Implementation

The overall process of transforming video data into images followed by numeric tabulation for selective data attributes classification is summarized in Fig. 1.

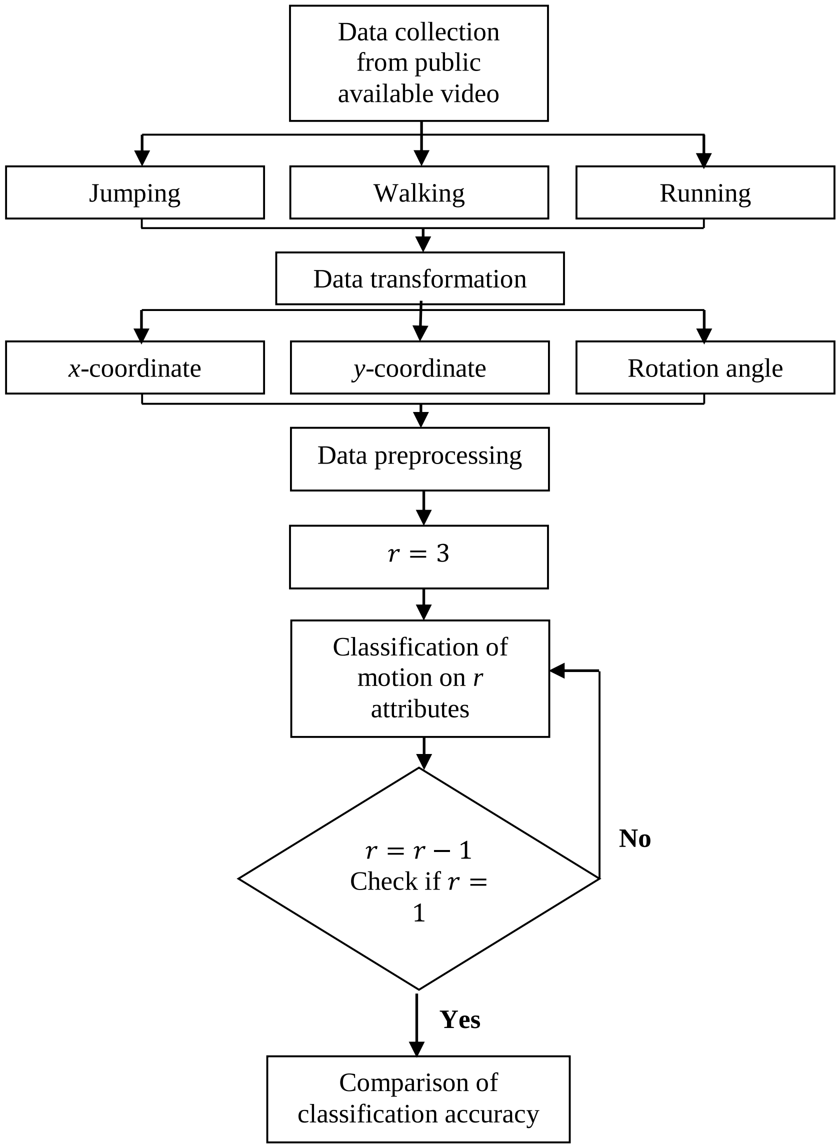


Fig. 1. Human motion classification framework.

Initially, the collected video clip was converted to static image files using the Movie Maker. These image files were transformed into numerical data for pre-processing analysis. Image transformation process involves identifying the human joints involved in performing the activities and the identified attributes were recorded based on *x*-coordinate, *y*-coordinate and rotation angle detailed in Section 2.3. Realistically, classification analysis is performed on the whole data set obtained from all identified attributes. However, quantitatively, one can classify the data based on compressed potential combinations of attributes (single to triple attributes).

More precisely, one can define the main selection criteria for reducing the attributes obtained. The loops of the selective attributes were generated based on possible combination counts by reducing an attribute each round until the minimal single attribute was considered. The selection criteria for determining the particular choice of attributes is further explained in Section 2.4. The classification of motion data can be divided into three classes based on the number of attributes, $r = 1$, 2 and 3. Data classification was performed on every potential attributes combination via Bayes, Function, Lazy, Meta, Rule and Trees built-in algorithms in WEKA tool. The classification accuracy was compared for single, double and triple attributes data to reflect the impact of a different number of attributes on classification accuracy.

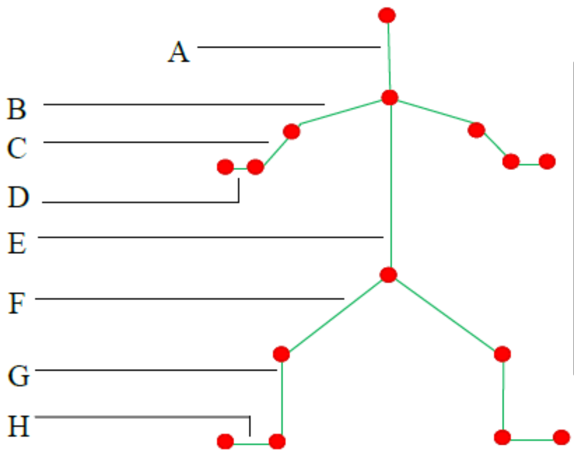
2.3. Motion transformation

The raw video files were transformed into image snapshots of 0.25 seconds interval followed by the numeric forms for further analysis. The reason to capture 0.25 seconds interval is to obtain an explicit pattern of the motion activities. The number of snapshot images chosen from different types of motion activity is shown in Table 1. Adopting the methods of Eichner et al. [6], Hoshino et al. [14], and Souvenir and Parrigan [15], the image files were transformed based on the most fundamental assumption that human motions can be ideally modelled into 2D rigid body segments or solid body by which image deformation is neglected. In practice, this is merely an approximation, since, in reality, human movements are in a 3D form where the *z*-axis is taken into account apart from the *x*-and *y*-plane. However, we have chosen to model the case study motion by 2D approximation because the third axis value was unavailable because only a single camera was used to capture the video from a particular angle.

Table 1. Raw data of original video.

Motion activity	Duration of video (s)	No. of snapshot images collected
Jumping	86	77
Walking	22	9
Running	18	16

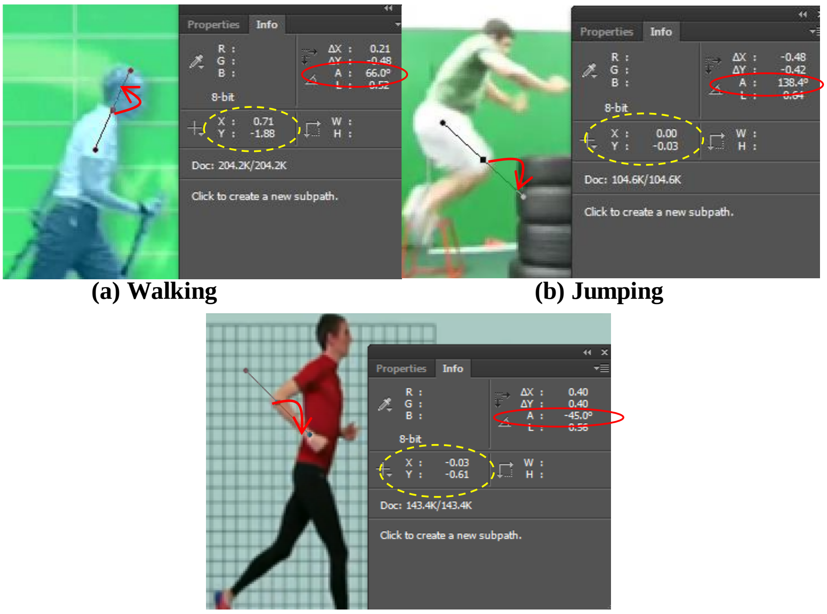
To transform the motion activities, the major attributes measured were determined at the data pre-processing level. The criterion was placed on the human body segments and joints to efficiently represent the overall human motions in performing different activities. Figure 2 shows a sketch of body segments and specific joints with markers placed on a 2D skeleton model for numeric measurement with Photoshop tool. The dots in the model represent the joints of the human body where *x* and *y*-coordinates were measured. The rotation angle of the body segment can also be determined from the solid lines.



A	Head
B	Upper arm
C	Lower arm
D	Palm
E	Upper body
F	Thigh
G	Lower leg
H	Foot

Fig. 2. Skeleton model of human.

Each snapshot image was measured at the body joints and segments that resulted in 15 variables: Head, upper arm (L/R), lower arm (L/R), palms (L/R), upper body, thigh (L/R), leg (L/R), foot (L/R), and orientation angle. The reference or stationary point was fixed at the pelvis for the reason that the body centre of gravity is located around the human pelvis. Figure 3 shows a sample 2D-coordinate (dash line circle) and rotation angle (solid line circle) measures for the three motion activities.



(a) Walking **(b) Jumping**

(c) Running

Fig. 3. Sample 2D-coordinate and rotation angle measurement.

The rotation angles of the body segments were measured horizontally. The counterclockwise direction was considered a positive value while the converse was considered a negative value. For instance, in Fig. 3, the sample rotation angle measured from the head was +66.0º; the rotation angle measured from the thigh was +138.4º while the rotation angle measured from the lower arm was -45.0º. Table 2 shows the numerical translated data upon data transformation processes. Section 2.4 presents the transformed data pre-processing approach using data elimination cum interpolation for imputation [16].

Table 2. Sample layout of raw data for jumping, walking and running motion.

			Upper-arm (degree)		**Lower-arm (degree)**		**Orientation angle (degree), i**	***Missing data (%)***
Time (s)	***Motion activity***	***Head (degree), a***	***Left, b1***	***Right, b2***	***Left, c1***	***Right, c2***		
0	Jump1	90.0	19.7	19.7	43.4	43.4	0	0
0.25	Jump1	54.5	-109.7	-109.7	-29.1	-29.1	0	0
2.00	Jump8	-172.9	-90		-95.4		170	40
0	Walk	67.9	-100.9	-120.8	-22.4	-127.3	0	0
7.5	Walk	68.0	-144.8	-90.9	-128.5	-9.5	0	0
0	Run	84.0	-124	-124	-53.9	-53.9	0	0
7.5	Run	81.0		-141.5		-45.9	0	20

2.4. Data pre-processing

Data pre-processing was performed on each motion-transformed data. The unnecessary data were discarded while missing data were treated as 'unknowns' for further investigation. According to Zhu and Zhang [17], the actual primary data are generally dirty, incomplete and inconsistent. To meet qualitative data mining analysis, data pre-processing is the prerequisite state to prepare and clean the data for further mining processes.

At this state, the percentage of missing data for each of the instances could be identified. The missing values in the raw dataset were the resultant of uncertain values from previous motion transformation due to hidden body segments and occlusion motions. It is found that the missing data contributes about 12.8% of the overall data in Table 2. Instances of above 30% missing values (indicated by shaded in a blue row in Table 2 were eliminated as the instances beyond this missing percentage do not generate enough information to produce good classification accuracy. The instances elimination processes resulted in 91.5% cleaned data.

The overall number of missing values was 8.5% of the data. Following Chan et al. [16], these missing values were imputed by data interpolation technique by fitting the best fundamental polynomial regression model shown in Eq. (1). For simplicity purposes, fundamental polynomial regressions up to the third order, linear, quadratic and cubic models were attempted.

$$Y = b_0 + b_1 X + b_2 X^2 + \cdots + b_n X^n \tag{1}$$

where $n = 1{,}2{,}3$, X = predictor and Y = respondent.

To determine the most appropriate polynomial fitting choice among the three, R^2 and p-value were used as the evaluation metrics. R^2 measures the fit of the model on the item respondents, whereas p-value determines the significance of the model developed for the specific attribute. According to Goodman [18] and Steel and Torrie [19], a low p-value with high R^2 value should be the good choice since this combination indicates the significance of the model. A sample R^2 and p-value evaluation analysis for jumping motion is shown in Table 3. The best-selected model was used to impute unknown values in Table 2.

Table 3. Example of R^2 and p-value evaluations of jumping motion.

Model	Left upper arm		Left lower arm		Left palm	
	R^2 (%)	***p-value***	***R^2 (%)***	***p-value***	***R^2 (%)***	***p-value***
Linear	0.7	0.86	57.4	0.048	75.5	0.005
Quadratic	89.0	0.005	59.9	0.643	82.5	0.216
Cubic	94.6	0.174	77.5	0.223	83.7	0.626
Best model	Quadratic		Cubic		Linear	

2.5. Attribute selection criteria

The main attributes involved are the *x*-coordinate, *y*-coordinate and rotation angle. The attribute selection criterion for classifications was based on the combination rule to evaluate the possible combinations of *r* attributes from a set of three attributes, Eq. (2). Table 4 shows the attributes combinations based on a number of attributes. The three numbers of main attributes and its possible attributes combination are tabulated in Table 4. The classification performances of the combined attributes data were examined with the aid of WEKA tool as presented in Section 3.

$$C_r^3 = \frac{3!}{r!(3-r)!} \tag{2}$$

where *r* = number of attributes.

Table 4. Potential combinations of data attributes.

Combinations	Potential combination	Attribute set
Single attribute (*r* = 1)	$C_1^3 = 3$	{*x*-coordinate};{*y*-coordinate}; {rotation angle}
Double attribute (*r* = 2)	$C_2^3 = 3$	{*x*, *y*-coordinate}; {*x*-coordinate, rotation angle}; {*y*-coordinate, rotation angle}
Triple attribute (*r* = 3)	$C_3^3 = 1$	{*x*-coordinate, *y*-coordinate, rotation angle}

3. Results and Discussion

3.1. Motion classification

The study data were classified based on types of motion: walking, running and jumping. The classification performances were demonstrated from the potential combinations of data attributes. To investigate the impact of a different number of combined attributes towards its classification accuracy, the classified data were considered based on (a) single, (b) double and (c) triple attributes. The classification accuracies presented are the average classification accuracies obtained from six built-in classifiers' (Bayes, Function, Lazy, Meta, Rule and Trees) strength in WEKA.

For a single variable, the data attribute of the rotation angle, *x*-coordinate and *y*-coordinate were subjected to classification processes separately. The classification results of the single attribute: {*x*-coordinate}, {*y*-coordinate} and {rotation angle} is shown in Fig. 4. Results show that the classification accuracies of *y*-coordinate are the lowest while *x*-coordinate and rotation angle is almost similar for Meta, Rule and Trees methods. Hence, it can be concluded that *y*-coordinate cannot stand alone in human motion analysis, as the data classification was not well performed for most of the classifiers.

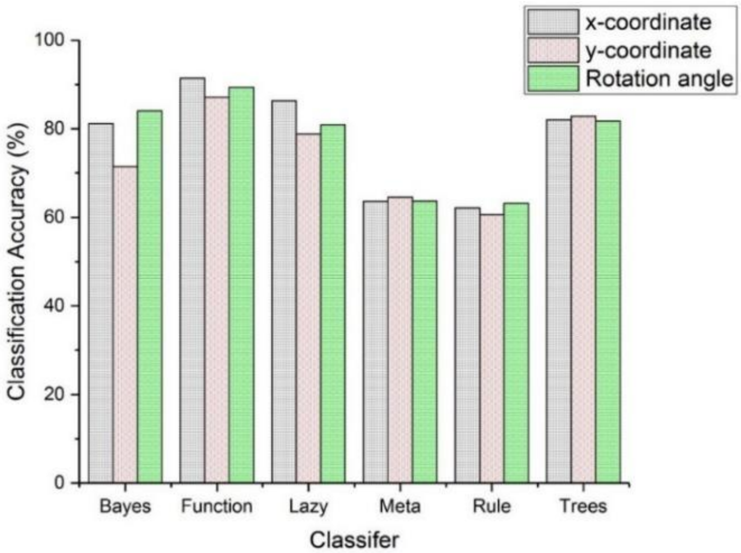


Fig. 4. Average classification accuracy by classifier category on single attribute data.

For two attributes classification, there were three potential combinations observed: {*x*-coordinate, *y*-coordinate}, {rotation angle, *x*-coordinate} as well as {rotation angle, *y*-coordinate}. The average classification accuracy for these combinations is shown in Fig. 5. It can be observed that the classification accuracy of {rotation angle, *y*-coordinate} shows the lowest values for most of the classifiers except for Rule. The Lazy method has performed well for a combination of {rotation angle, *x*-coordinate} compared to the other two combinations of attributes.

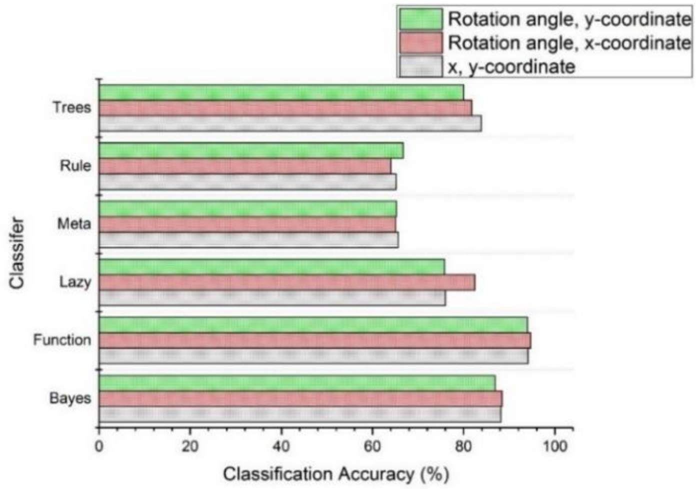


Fig. 5. Average classification accuracy by classifier category on double attribute data.

For three attributes classification accuracy, the fusion of rotation angle, *x*-coordinate and *y*-coordinate was included as shown in Fig. 6. The average classification accuracy reaches the highest value by using the Function method while the lowest value was observed in the Meta method. It is also noted that the Function method always performs the best compared to other classifiers as observed from Figs. 4 to 6 and it achieved the classification accuracy of 96.32% in tribute attributes. Comparing with the results obtained in Yan et al. [10], the highest overall accuracy was 89.2% by focusing on the orientation of the back, arm and legs of the human body.

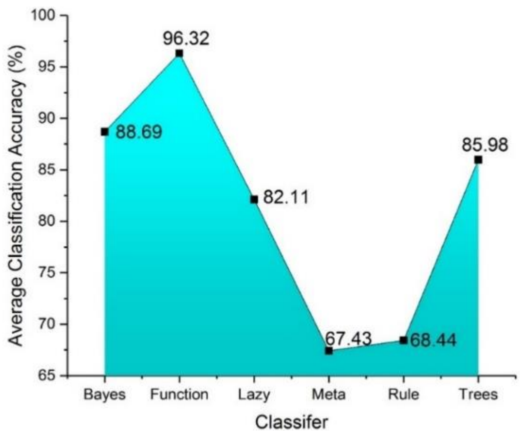


Fig. 6. Average classification accuracy by classifier category on triple attributes.

3.2. Classification performances comparisons

The results obtained from single to triple attributes classifications are summarized in Table 5. Generally, the average classification accuracy has increased from single attribute to triple attribute on average by 5.44%. The findings also show that triple attributes present the highest average classification accuracy of 81.50% compared to double and single attribute data of 79.10% and 76.06% respectively.

Table 5. Average classification accuracy by classifier (%) on different number of attribute.

Classifier	Number of attributes		
	Single	*Double*	*Triple*
Bayes	78.91	87.81	88.69
Function	89.29	94.26	96.32
Lazy	80.01	80.08	82.11
Meta	63.93	65.29	67.43
Rule	62.00	65.30	68.44
Trees	82.20	81.88	85.98
Average	**76.06**	**79.10**	**81.50**

Figure 7 identifies the suitable number of attributes that yield the highest classification accuracy. The *x*-axis represents the types of the attribute used in the classification process while the classification accuracy from six classifier algorithms is indicated in the *y*-axis. The observation shows that the average classification accuracy as labelled in Fig. 7 reaches the optimum value for triple attributes combination: {*x*-coordinate, *y*-coordinate, rotation angle} which is indicated in the region with an average classification accuracy of 81.50%. Besides, Function, Bayes, Trees and Lazy classifiers were exceptional when compared with Meta and Rule classifiers. The reason of low performance in Meta and Rule classifier is due to the regression-based and statistic function face difficulty to apply on the random motion. It is also observed that the average classification accuracy is directly proportional to the number of attributes considered for each of the classifiers presented in Fig. 7, and this indicated that triple attributes have provided sufficient information for classification as compared to single and double attributes.

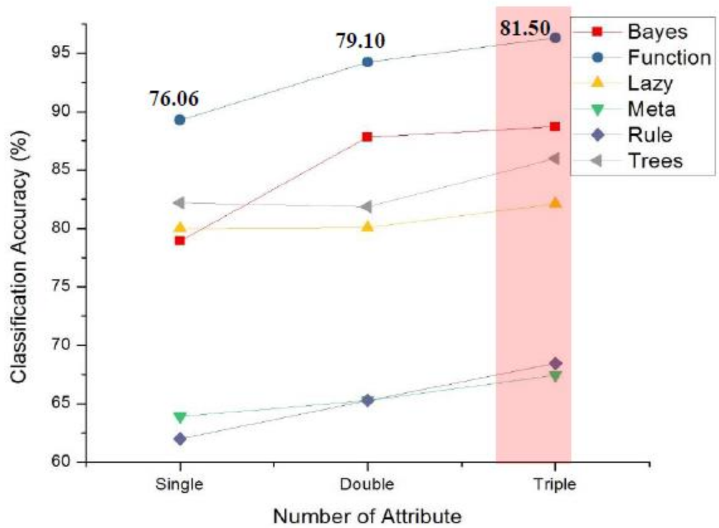


Fig. 7. Average classification performances on different number of attributes.

3. Conclusion

The impact of a number of attributes on the accuracy of human motion classification was investigated. The study considers possible attributes combinations: single, double and triple attributes as the subset of the collected data parameters involving the *x*-coordinate, *y*-coordinate and rotation angle. Overall results showed that the triple attribute combination performed best with an average classification accuracy of 81.50% compared to the single and double attributes of 76.06% and 79.10%, respectively. The findings also suggest that the classification accuracy increases in direct proportional relation with the number of attributes considered for the study case. This study has highlighted that classification performances are much dependent on the number of potentially combined data attributes. In future, these research needs to be extended to further investigate the robustness of the proposed method on a higher number of attributes to obtain optimum classification results.

Nomenclatures

b	Coefficient of polynomial, Eq. (1)
L	Left
n	Degree of polynomial, Eq. (1)
r	Number of attributes, Eq. (2)
R	Right
X	Predictor, Eq. (1)
Y	Respondent, Eq. (1)

Abbreviations

2-D	2-Dimensional
3-D	3-Dimensional
WEKA	Waikato Environment for Knowledge Analysis

References

1. Tong, M.; Liu, Y.; and Huang, T.S. (2007). 3D Human model and joint parameter estimation from monocular image. *Pattern Recognition Letters*, 28(7), 797-805.
2. Cameron, J.; and Lasenby, J. (2008). *Articulated motion and deformable objects*. Estimating human skeleton parameters and configuration in real-time from markered optical motion capture. Germany: Springer Berlin Heidelberg, 92-101.
3. Liu, M.; Liu, H.; and Chen, C. (2017). Enhanced skeleton visualization for view invariant human action recognition. *Pattern Recognition*, 68(C), 346-362.
4. Cao, W.; Che, R.; and Ye, D. (2007). Estimation of the centre of rotation and 3D motion parameters from stereo sequence images and virtual validation using three-COMERO. *Pattern Recognition Letters*, 28(13), 1593-1599.
5. Shi, Z.; Zhang, Q.; Tu, J.; Wang, Z.; and Zhang, X. (2012). Vision stability of four-legged robot based on the feedback of motion parameters. *Procedia Engineering*, 29, 3250-3255.

6. Eichner, M.; Marin-Jimenez, M.; Zisserman, A.; and Ferrari, V. (2012). 2D articulated human pose estimation and retrieval in (almost) unconstrained still images. *International Journal of Computer Vision*, 99(2), 190-214.
7. Poularakis, S.; Avgerinakis, K.; Briassouli, A.; and Kompatsiaris, I. (2017). Efficient motion estimation methods for fast recognition of activities of daily living. *Signal Processing: Image Communication*, 53(C), 1-12.
8. Zhao, Y.; Di, H.; Zhang, J.; Lu, Y.; Lv, F.; and Li, Y. (2017). Region-based Mixture Models for human action recognition in low-resolution videos. *Neurocomputing*, 247, 1-15.
9. Zhou, H.; You, M.; Liu, L.; and Zhuang, C. (2017). Sequential data feature selection for human motion recognition via Markov blanket. *Pattern Recognition Letters*, 86, 18-25.
10. Yan, X.; Li, H.; Wang, C.; Seo, J.; Zhang, H.; and Wang, H. (2017). Development of ergonomic posture recognition technique based on 2D ordinary camera for construction hazard prevention through view-invariant features in 2D skeleton motion. *Advanced Engineering Informatics*, 34, 152-163
11. GymstickFitness. (2010). Gymstick nordic walking technique. Retrieved June, 29, 2012, from http://www.youtube.com/watch?v=EuuCAipLeQY.
12. PlaymakersOkemos. (2009). Good form running. Retrieved June 28, 2012, from http://www.youtube.com/watch?v=Tx6x2cD6Y8Q.
13. VerticalJumpKing. (2011). Vertical jump for basketball training. Retrieved June 29, 2012, from http://www.youtube.com/watch?v=HKOevvmGUOQ.
14. Hoshino, R.; Arita, D.; Yonemoto, S.; and Taniguchi, R.-i. (2002). *Articulated motion and deformable objects* Real-time human motion analysis based on analysis of silhouette contour and color blob. Springer Berlin Heidelberg.
15. Souvenir, R.; and Parrigan, K. (2009). Viewpoint manifolds for action recognition. *EURASIP Journal on Image and Video Processing*, Article ID 738702, 1-13.
16. Chan, C.K.; Loh, W.P.; and Rahim, I.A. (2013). Data elimination cum interpolation for imputation: A robust preprocessing concept for human motion data. *Procedia-Social and Behavioral Sciences*, 91, 140-149.
17. Zhu, Y.-l.; and Zhang, J. (2012). Research on data preprocessing in credit card consuming behavior mining. *Energy Procedia*, 17, Part A, 638-643.
18. Goodman, S.N. (1999). Toward evidence-based medical statistics, 1: The p-value fallacy. *Annals of Internal Medicine*, 130(12), 995-1004.
19. Steel, R.G.D.; and Torrie, J.H. (1960). *Principles and procedures of statistics with special reference to the biological sciences*. McGraw Hill.