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Human gait recognition using orthogonal least square as feature selection

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ABSTRACT

This study investigates the potential gait features that are related to human recognition using orthogonal least square (OLS). Firstly, video of 30 subjects walking in oblique view was recorded using Kinect. Next, all 20 skeleton joints in 3D space were extracted and further selected using OLS. Additionally, SVM with linear, polynomial and radial basis function (RBF) kernel was used to classify the selected features. As consequences, OLS was proven to be able to identify the significant features using all three kernels of SVM since all recognition accuracy attained is higher as compared to the original gait features. Results attained showed that the highest recognition accuracy was 90.67% using 48 skeleton joint points for SVM with linear as kernel, followed by 46 skeleton joint points for SVM with RBF kernel namely 88.33% and accuracy of 86.33% for 38 skeleton joint points using polynomial kernel.

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1. INTRODUCTION

Recently, study on recognition of human gait using features extracted from Kinect sensor was extensily explored and investigated. This is because the usage of Kinect in data acquisition could simplifies process of extracting gait features since Kinect sensor automatically tracks walking human by generating all coordinate of 20 skeleton joints in the 3D space [1-3]. Furthermore, gait features that are generated from the Kinect was proven significant for human recognition purpose as reported by [4-6]. Parameter such as attire, lighting along with walking view are commonly investigated in order to develop robust recognition technique.

Initially, recognition of human gait using Kinect has been explored specifically in lateral view. For instance, nine subjects were required to walk from right to left, in front of the Kinect for eight times [7, 8]. Then, 11 sets of static features consisting of height, length of legs, torso, both lower legs, both thighs, both upper arms and both forearms, and two sets of dynamic features; the length of step and the speed were extracted. The researchers further examined the potential gait features related to human recognition using Naïve Bayes, One Rule (1R) and C4.5 algorithm. The outcome was a high recognition accuracy of 91% using combination of four static gait features and Naïve Bayes as classifier. The four static gait features identified as significant were height, length of legs, length of torso and length of the left upper arm. Conversely, recognition of human gait in lateral view was further investigated in the study of [9-11]. In these studies, combination of dynamic and static features was found to be highly significant for human recognition as compared to static and dynamic features solely. Additionally, recognition of human gait was further extended to other gait views such as frontal, oblique and multi-view. Similar to lateral view, human gait could be highly recognize using fusion of static and dynamic features with classifiers such as Multi-Layer Perceptron (MLP), Support Vector Machine (SVM) [12-15] and k-Nearest Neighbor (kNN) [16], for both frontal view and multi-view [17]. Meanwhile, for oblique view, to the best of our knowledge, only one study reported on the recognition of human gait in oblique view. The researchers performed recognition of 10 subjects walking in lateral, oblique and frontal views in front of the Kinect using WEKA application along with LibSVM and One Class Classifier were employed to classify gait pattern according to its group. The results attained showed that the most significant feature was the fusion of seven static features; the length of the right and left shoulder, height, the length of the right arm and the length of the right knee and right foot and the length of the right hip. Conversely, orthogonal least square (OLS) has been used to select the most significant features in pattern recognition area as reported in [18-20]. Primarily, OLS algorithm has been utilised in system identification [21, 22] and structure of classifier model [23, 24]. Though OLS has never been used in gait recognition for feature selection, based on past researches that reported good performance of OLS as discussed in [18, 19], the potential of OLS as feature selection will be investigated in this study. Therefore the recognition of human gait in oblique view along with OLS as features optimization and Support Vector Machine (SVM) as classifier will be further explored and investigated.

2. RESEARCH METHOD

Figure 1 depicts the recognition of human gait using OLS and SVM for oblique view. Firstly, video of walking human was recorded by the Kinect during data acquisition. The recorded video was captured at 30 frames per second with resolution of 640 x 480. Then, skeleton joints generated from the Kinect are extracted. In order to identify skeleton joints related to human gait recognition, OLS is used to select the significant skeleton joints and further classify by SVM. To evaluate the significant skeleton joints, recognition accuracy is computed based on average of 10-cross validation method.

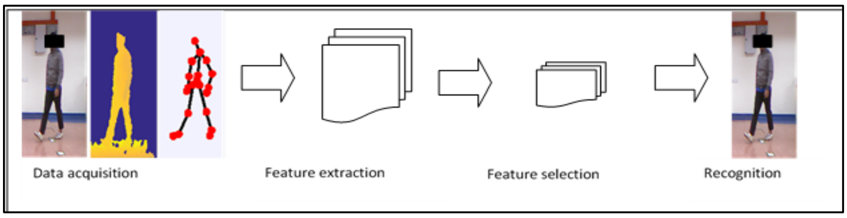

Figure 1. Recognition of human gait for oblique view

During data acquisition stage, 30 subjects were required to walk obliquely, in front of the Kinect, as shown in Figure 2. Here, layout measurement employed was based on the standard measurement of Kinect. The red area indicates the covered monitoring area and area of walking by subjects is recorded. In order to gain normal walking patterns, the participants began walking outside of the covered area. The subjects were requested to walk repeatedly for 10 times and no restriction on clothing types. In addition, the participants are required to walk naturally using their comfortable walking style and speed. Next, skeleton joints within a full gait cycle are extracted in the feature extraction stage. This stage involves five steps; removal of empty video frames, normalization of skeleton joints, detection of gait cycle, synchronization of frame number and lastly, extraction of skeleton joints. In the first step, empty video frames recorded during data acquisition are removed. Then, skeleton joints are normalized at a constant size. From observation, an inconsistency size of human skeleton attained as the participant moves toward the Kinect. Here, the size of human skeleton at a half of the trimmed video was chosen as the fix size. In addition, relative movement of skeleton joints was computed by considering head joint as the reference point. After that, a full gait cycle was detected by tracing three consecutive local minima in the vector of distance between the joint of left ankle and right ankle [4]. The distance vector was computed using Euclidean distance (1), in z-axis of the joints, and then filtered and smoothed using Savitzky-Golay moving average algorithm as:

$$d(a,b) = \sqrt{(\mathrm{a_z} - b_z)^2} \quad (1)$$

where a is the joint of left ankle and b is the joint right ankle.

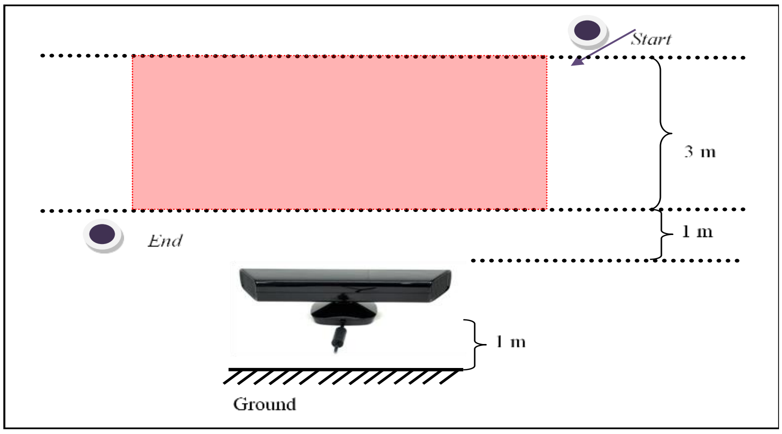

Figure 2. Recording area with its layout measurement

As consequences, one to two gait cycles with various frame numbers were attained for all walking sequences. The various frame numbers (12 to 26 frames) further can lead to intricacy in the recognition stage. Therefore, in the synchronization of frame number stage, spline interpolation was employed to standardize the frame numbers at a maximum frame number (26 frames). Lastly, in the feature extraction stage, skeleton joints in each xyz-axis; which also known as skeleton joint points, as listed in Table 1 were extracted within a full gait cycle, using (2).

$$Feature\ vector = (j_{x_n} j_{y_n} j_{z_n} \times\ m) \times s \tag{2}$$

where j_{xn} = number of skeleton joint in x-coordinate, j_{yn} = number of skeleton joint in y-coordinate, j_{zn} = number of skeleton joint in z-coordinate, m = number of frame and s = number of sample.

Table 1. Skeleton Joint Point with Its Label

Number of joint point	Name of skeleton joint point	Number of joint point	Name of skeleton joint point	Number of joint point	Name of skeleton joint point
1	Hip_center_x	21	Hip_center_y	41	Hip_center_z
2	Spine_x	22	Spine_y	42	Spine_z
3	Shoulder center_x	23	Shoulder center_y	43	Shoulder center_z
4	Head_x	24	Head_y	44	Head_z
5	Shoulder left_x	25	Shoulder left_y	45	Shoulder left_z
6	Elbow left_x	26	Elbow left_y	46	Elbow left_z
7	Wrist left_x	27	Wrist left_y	47	Wrist left_z
8	Hand left_x	28	Hand left_y	48	Hand left_z
9	Shoulder right_x	29	Shoulder right_y	49	Shoulder right_z
10	Elbow right_x	30	Elbow right_y	50	Elbow right_z
11	Wrist right_x	31	Wrist right_y	51	Wrist right_z
12	Hand right_x	32	Hand right_y	52	Hand right_z
13	Hip left_x	33	Hip left_y	53	Hip left_z
14	Knee left_x	34	Knee left_y	54	Knee left_z
15	Ankle left_x	35	Ankle left_y	55	Ankle left_z
16	Foot left_x	36	Foot left_y	56	Foot left_z
17	Hip right_x	37	Hip right_y	57	Hip right_z
18	Knee right_x	38	Knee right_y	58	Knee right_z
19	Ankle right_x	39	Ankle right_y	59	Ankle right_z
20	Foot right_x	40	Foot right_y	60	Foot right_z

For standardization purpose, only gait features within one gait cycle for each walking sequence per participant was used for the next stage. In the feature selection stage, the OLS algorithm calculates Error Reduction Ratio (ERR) for each skeleton joint in the model. From these, the percentage reduction made by each skeleton joint with respect to the output Mean Squared Error (MSE) is derived. The significance of each skeleton joint is ranked according to its contribution in reducing error in the model. The higher the ERR value, the more significant the skeleton joint point is. In this study, the OLS is computed for m frames of each skeleton joint point. Hence, the input features for OLS computation was arranged for each frame as shown in (3):

$$f_{ik} = s \times j_{x_n} j_{y_n} j_{z_n} \tag{3}$$

where j_{xn} = number of skeleton joint in x-coordinate, j_{yn} = number of skeleton joint in y-coordinate, j_{zn} = number of skeleton joint in z-coordinate, s = number of sample.

In the OLS computation, the expected output y_k was computed as follows:

$$y_k = \sum_{i=1}^{m} f_{ik}\theta_i \tag{4}$$

where, m is the number of frame, f_{ik} is the input features; θ_i is the solution to the linear least squares problem for $i = 1, \dots, m$. With the use of Householder-based QR decomposition, the input features, f_{ik} is transformed into an auxiliary model as shown in (5).

$$y_k = \sum_{i=1}^{m} w_{ik} g_i \tag{5}$$

where, w_{ik} is orthogonal to one another and g_i are constant coefficients.

The estimates of the coefficients g_i are given by:

$$\widehat{g_\iota} = \frac{\sum_{k=1}^{N} w_{ik} y_k}{\sum_{k=1}^{N} w^2{}_{ik}} \tag{5}$$

and the error expression for ERR, err_i computed as:

$$err_i = \frac{\widehat{g_\iota}^2 \sum_{k=1}^{N} w^2{}_{ik}}{\sum_{k=1}^{N} y^2{}_k} \tag{6}$$

then, average err, ERR is computed as:

$$\mathrm{ERR} = \frac{err_i}{m} \tag{7}$$

The skeleton joint point with the highest ERR was arranged at the top and the lowest ERR was placed at the bottom. Further, the input feature was arranged using (2) with numbers of arranged skeleton joint points, starting from 2 to 60 skeleton joint points with incremental of 2.

As a result, various numbers of feature set were obtained. In the recognition stage, SVM with linear, polynomial and Radial Basis Function (RBF) kernel were employed as the classifiers. Upon several experimental analysis, regularization parameter (C) for linear kernel was significant to vary at 0.001, 0.01, 0.1, 1 and 10, for polynomial and RBF kernel at 0.00001 to 0.01 with 1 decade increments and 10 to 100 with 10 increments, respectively. In addition, polynomial order (d) of polynomial kernel was experimented at 2 and 3 and sigma (σ) for RBF kernel varied from 10 to 200. For the purpose of the evaluation of recognition performance and parameter selection of the classifier model [22], the 10-fold cross validation [25, 26] was used.

3. RESULTS AND ANALYSIS

In this section, the results attained based on the proposed methodology will be elaborated and discussed. As tabulated in Table 2, it can be observed that the rank of skeleton joint points after the implementation of OLS. Obviously, the joint of hip center in x-axis dominates the first rank as it attained the highest ERR. Furthermore, it can be seen that most of skeleton joints in x-axis placed at the first 30 rank, followed by skeleton joints in y-axis and z-axis, respectively.

Figure 3 shows the recognition accuracy attained at the optimal SVM model. High recognition accuracy attained at 48 skeleton joint points for SVM with linear kernel (90.67%), 44 skeleton joint points for SVM with RBF kernel (88.33%) and 38 skeleton joint points for SVM with polynomial kernel (86.33%). In order to verify the effectiveness of OLS as feature selection, recognition accuracy for features without OLS was computed too.

Figure 4 depicts the comparison of recognition accuracy between the original features and OLS features. As can be observed, recognition accuracy are enhanced using features selected by OLS, for all SVM kernels category.

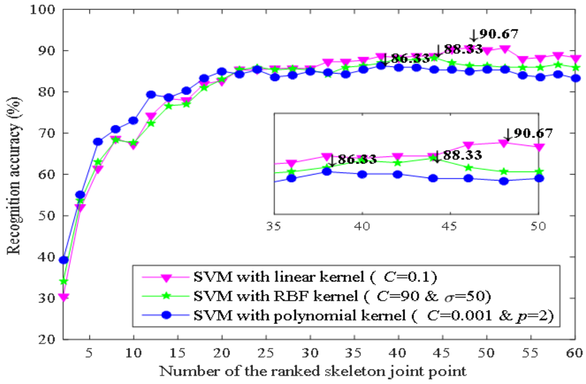

Figure 3. Recognition accuracy for various numbers of skeleton joint points accordance to OLS rank

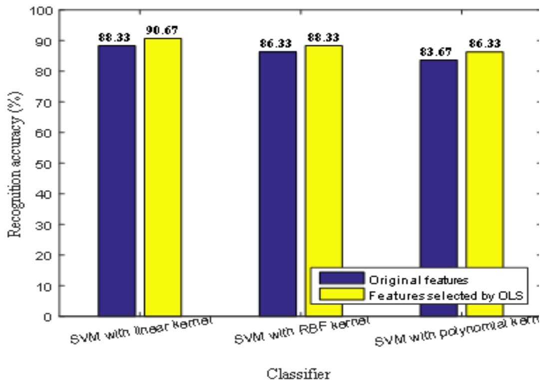

Figure 4. Recognition accuracy attained using original features and features selected by OLS for SVM

Table 2. Rank of Skeleton Joint Points after OLS Implementation

Joint label	Joint name	ERR	Joint label	Joint name	ERR
1	Hip_center_x	0.699097276	55	Ankle left_z	0.000636189
21	Hip_center_y	0.085875078	26	Elbow left_y	0.000621815
4	Head_x	0.042695157	31	Wrist right_y	0.000621299
3	Shoulder center_x	0.019806264	57	Hip right_z	0.000615943
5	Shoulder left_x	0.015747802	29	Shoulder right_y	0.000592885
10	Elbow right_x	0.014847255	38	Knee right_y	0.000588331
23	Shoulder center_y	0.013521678	43	Shoulder center_z	0.000537843
9	Shoulder right_x	0.004801643	60	Foot right_z	0.000521329
17	Hip right_x	0.003904192	48	Hand left_z	0.000487427
13	Hip left_x	0.003405773	47	Wrist left_z	0.000480826
8	Hand left_x	0.003336582	28	Hand left_y	0.000467799
14	Knee left_x	0.003330543	37	Hip right_y	0.000453269
11	Wrist right_x	0.003307623	46	Elbow left_z	0.000438526
7	Wrist left_x	0.003139608	41	Hip_center_z	0.000421997
27	Wrist left_y	0.002716615	45	Shoulder left_z	0.000415265
2	Spine_x	0.002675057	51	Wrist right_z	0.000407073
22	Spine_y	0.002644155	53	Hip left_z	0.000402531
6	Elbow left_x	0.002040701	42	Spine_z	0.000383909
34	Knee left_y	0.001630870	36	Foot left_y	0.000355970
12	Hand right_x	0.001394476	50	Elbow right_z	0.000353017
19	Ankle right_x	0.001333185	54	Knee left_z	0.000348224
16	Foot left_x	0.001321263	49	Shoulder right_z	0.000346255
15	Ankle left_x	0.001209764	58	Knee right_z	0.000319731
35	Ankle left_y	0.000919835	18	Knee right_x	0.000296275
20	Foot right_x	0.000909513	32	Hand right_y	0.000266994
25	Shoulder left_y	0.000821467	59	Ankle right_z	0.000239201
24	Head_y	0.000785205	44	Head_z	0.000220702
40	Foot right_y	0.000736709	56	Foot left_z	0.000208776
33	Hip left_y	0.000674316	39	Ankle right_y	0.000201806
30	Elbow right_y	0.000654517	52	Hand right_z	0.000198280

4. CONCLUSION

In conclusion, recognition of human gait in oblique view using features selected by the optimized OLS and SVM has been discussed in this study. The results showed that the combination of OLS and SVM with linear kernel contributed to the highest recognition rate namely 90.67% with 48 skeleton joint points as compared to the other two kernels. Future work includes investigating the human gait recognition using other feature selection method namely linear discriminant analysis and other classifiers specifically Naive Bayesian classifier and Deep Learning Neural Network.

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