Human gait recognition using orthogonal least square as feature selection

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Article Info

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.

Keywords:
Human gait recognition
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1. INTRODUCTION

Recently, study on recognition of human gait using features extracted from Kinect sensor was extensively 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](image)

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:

\[ d(a, b) = \sqrt{(a_z - b_z)^2} \]  

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

$$Feature \ vector = (j_{xn}j_{yn}j_{zn} \times m) \times s$$ (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.

| 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):
where \( f_{ik} = s \times j_{xn} \times j_{yn} \times j_{zn} \)  

\[ (3) \]

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:

\[
y_k = \sum_{i=1}^{m} f_{ik} \theta_i
\]

\[ (4) \]

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

\[
y_k = \sum_{i=1}^{m} w_{ik} g_i
\]

\[ (5) \]

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

The estimates of the coefficients \( g_i \) are given by:

\[
\hat{g}_i = \frac{\sum_{k=1}^{N} w_{ik} y_k}{\sum_{k=1}^{N} w^2_{ik}}
\]

\[ (5) \]

and the error expression for ERR, \( err_i \) computed as:

\[
err_i = \frac{\sum_{k=1}^{N} w^2_{ik} y^2_k}{\sum_{k=1}^{N} y^2_k}
\]

\[ (6) \]

then, average ERR, \( ERR \) is computed as:

\[
ERR = \frac{\sum_{i=1}^{m} err_i}{m}
\]

\[ (7) \]

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 \( (\sigma) \) 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.
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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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