Classification of Gait Biometric on Identical Twins
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ABSTRACT
This is the first classification analysis of gait as a biometric on identical twins. In this paper, a small sample viability analysis is performed on using gait as a biometric in recognition of identical twins. The motivation behind this paper is that identical twins have high face similarities, where video-based surveillance system relying on face biometric alone may have difficulty in distinguishing between them. Our gait features are the angular displacement walking trajectories from gait videos. Next, this paper proposes to apply a trajectory normalization by a Bezier spline root-finding and re-sampling to deal with the unequal speed of the walking trajectories. Then, classification using linear discriminant analysis (LDA) and $k$-nearest neighbour are applied where the best average correct classification rate (CCR) is 76\% when classifying an individual twin as a unique individual.

Keywords: Twins’ Biometric, Gait Biometric, Trajectory Normalization, Bezier Spline

1. Introduction
Gait is a biometric based on the way human walks. Gait is believed to be unique to every person (Murray, 1967) and every person is said to have “their own idiosyncratic ways of walking”. It has received much interest due to its capabilities for use in video-based surveillance systems since it is non-invasive and does not require human cooperation. Its motion is extracted from videos as individual signatures for recognition (Bhanu and Han, 2003) (Boyd and Little, 2005) (Boulgouris et. al, 2005) (Nixon and Carter, 2006) (Huang and Tan, 2010); hence it can be captured at low resolution when common closed-circuit cameras (CCTVs) are used. Additionally, a person’s gait is difficult to conceal; it comes naturally to a person. In fact, an individual who walks awkwardly may bring suspicions due to his/her conspicuous gait.

The face recognition system is another system that operates from a distance (Jain et. al, 2005) (Chang et. al, 2005) (Yang et. al, 2007). To some extent, when an individual face is similar, as in identical twins; this poses a risk to a face-based surveillance system. Gait may overcome drawbacks arisen from the face recognition system. As has been shown by research of Phillips et. al (2011), where three top face recognition systems from the 2010
Multiple Biometric Grand Challenge has been evaluated with 5% equal error rate. This NIST study has concluded that in practical application, the current face technology may not be able to distinguish identical twins and powerful algorithms are still needed to discriminate the faces of twins.

Thus far, the soft biometrics of faces have been proposed to be the solution to single out an individual twin. As has been shown in a research by Park and Jain (2010), where scars and moles are proposed as the ‘soft’ features. However, this may require high resolution camera systems, where surveillance systems may be lacking. Similar advanced camera systems are required by research from Rychlik (2011), where 3D faces data of identical twins and non-identical twins have been applied to the Principal Component Analysis (PCA).

The interest in biometric of twins extends to research on irises as well as fingerprints (Sun et al, 2010). On the contrary, no study on gait has been looked into as a potential human biometric in recognition of identical twins. This work aims to look into this potential by performing a small sample classification analysis. This is the first on such analysis within this research area.

This paper is laid out as follows: the next section is an explanation of the data that will be used; the data requirements and how they are collected including the description of the extracted features. Our features are the angular displacement of walking trajectories from videos. Next, a detailed description of a trajectory normalization process on the features by the Bezier spline is presented. This is a must since each individual’s trajectory is having unequal lengths due to differences in walking speed. The section after that describes the results of the classification analysis with discussion. There are two analyses performed, where (1) is a classification of both twins as one unique pair and (2) is a classification of each twin as a unique individual. All processes are illustrated in Fig.1. Finally the paper is concluded in the last section.

![Fig. 1. All processes involved in this paper.](image)

2. Feature Extraction

Videos of 12 pairs of identical twins are gathered, where they are young adults, aged between 16-25 years old. This ensures an invariant analysis against age, since age has been shown to affect gait by research in medical domain (Grieve and Gear, 1966). Also, to ensure
invariability against body weights; the selected twins are having weights within the ‘healthy’ BMI (Body Mass Index). This carefully establishes a better height-to-weight ratio rather than weight measure alone. The twins walk at a normal pace without carrying objects. The video camera captures the twins at full height from sideways. This follows closely the setup of established medical research on gait (Murray, 1967) (Rose, 1983) (Sutherland, 2001) and other gait databases (Soton, 2002) (Casia, 2002). To establish invariant walking on each leg, the twins have to walk from left to right of the horizontal camera view and vice versa. The filming is done indoors to eliminate any potential illumination problems and filmed with non-cluttered homogeneous coloured wall as its background. Each video has at least one and a half gait cycle as defined by Murray (1967). Then, each video is processed for its image-frames as in Fig.2.

The data that is being gathered are the angular displacements of the limbs while moving. This follows the successful research by previous research in both medical and biometric domains (Yam et. al, 2004) (Bouchrika et. al, 2008) (Lim et al., 2007). By tracking the person’s leg at each frame, a straight line is fitted on the thigh and the lower limb. Four coordinates are extracted; two from each straight line and angular measurements, $\alpha$ and $\beta$ are calculated. The first measurement, $\alpha$ gives the rotational angle of the thigh from side to side and the latter ($\beta$) measures the rotational angle for the lower leg from side to side. These measurements as shown in Fig.2, make up sample of two separate signals for each individual as below:

Given a video of an individual, $i$ let $L_i$ be the lengths of $\alpha$ and $\beta$ with respect to time instance $t_{i[n]}$, as

$$\alpha_i = \alpha(t_{i[n]}) \quad \alpha \in \left[ -\frac{\pi}{2}, \frac{\pi}{2} \right]$$

(1)

$$\beta_i = \beta(t_{i[n]}) \quad \beta \in \left[ -\frac{\pi}{2}, \frac{\pi}{2} \right]$$

(2)

The forward movement of the leg is assigned positive values and vice versa. The midpoints of $\alpha$ and $\beta$, at $0^\circ$ is when the foot of the tracked leg falls flat on the ground, this position is called as the “at vertical” position.
3. Feature Normalization

Each individual’s trajectory is having unequal lengths due to differences in walking speed. To establish invariance to the walking speed, a cycle normalization task is proposed to ensure a robust analysis. Murray (1967) has defined a complete gait cycle to begin from a heel-strike of one leg to the next heel-strike of the same leg, Fig.3. Research in previous literature has been following this definition in their analyses. Due to ambiguity in determining the time of heel-strike, it is proposed that the beginning of the gait cycle is from the “at vertical” position of the individual to the successive “at vertical” position (within two steps) as illustrated in Fig.4.
Fig. 4. Our proposed gait cycle extraction that starts from the individual to be at vertical and the successive at vertical position.

The “at vertical” positions can be found by locating the roots of the $\alpha$ and $\beta$ signals. However, there is a need to ensure each signal is smooth between the values of positive and negative before locating the root. Thus, this paper proposes to apply a Bezier polynomial smoothing around these points. Bezier polynomials have been widely used as smoothing splines in graphics (Yamaguchi, 1998). It requires four points, where two of these are endpoints that are fitted with the smooth line while two others (the in-between) are control points that guide where the line will be fitted. To locate the roots, two points from each positive and negative angle values are selected. These are the $[n-2]$, $[n-1]$, $[n]$, and $[n+1]$ of $t[n]$. The mathematical formulation for the Bezier polynomials for $\alpha$ is shown next; the same applies to $\beta$ signals.

Given four time instances with their corresponding angle values $(\alpha_{[n-2]}, t_{[n-2]})$, $(\alpha_{[n-1]}, t_{[n-1]})$, $(\alpha_{[n]}, t_{[n]})$, and $(\alpha_{[n+1]}, t_{[n+1]})$, the Bezier polynomials are defined as,

$$t(\tau) = t_{[n-2]} + b_1 \tau + c_1 \tau^2 + d_1 \tau^3$$

$$\alpha(\tau) = \alpha_{[n-2]} + b_\alpha \tau + c_\alpha \tau^2 + d_\alpha \tau^3$$

where,

$$b_1 = 3(t_{[n]} - t_{[n-2]})$$
$$c_1 = 3(t_{[n]} - t_{[n-1]}) - b_1$$
$$d_1 = t_{[n+1]} - t_{[n]} - b_1 - c_1$$
$$b_\alpha = 3(\alpha_{[n]} - \alpha_{[n-2]})$$
$$c_\alpha = 3(\alpha_{[n]} - \alpha_{[n-1]}) - b_\alpha$$
$$d_\alpha = \alpha_{[n+1]} - \alpha_{[n]} - b_\alpha - c_\alpha$$

The Bezier polynomials solve for three $\tau$ values when $\alpha(\tau) = 0$. The actual roots will be the real $\tau$ values within $0 \leq \tau \leq 1$. Then a gait cycle is extracted between successive roots and re-sampled to $m = 30$ number of points as in Fig.5 ($\alpha$ signal) and Fig.6 ($\beta$ signal). The algorithm that applies this Bezier root-finding is outlined below:
Algorithm Bezier_Roots_Finding
Input: \( \alpha \) and \( \beta \)
Output: root, \( \tau \)
Initialization of flag:
\[
\text{if } \alpha_{[n]} < 0, \text{ then} \\
\quad \text{flag} = 0; \\
\text{else} \\
\quad \text{flag} = 1;
\]
Loop:
\[
\text{for each value } n \text{ of } \alpha_{[n >= 2]}, \text{ do} \\
\quad \text{set } \text{diff} = (\alpha_{[n]} - \alpha_{[n-2]}); \\
\quad \text{if } \text{diff} < 0 \text{ and flag} = 1, \text{ then} \\
\quad \quad \text{change flag} = 0; \\
\quad \quad \text{solve Bezier;} \\
\quad \text{else if } \text{diff} > 0 \text{ and flag} = 0, \text{ then} \\
\quad \quad \text{change flag} = 1; \\
\quad \quad \text{solve Bezier;} \\
\quad \text{end if} \\
\text{end for} \\
\text{return root.}
\]

Fig. 5. A complete gait cycle extraction of an \( \alpha \) signal for a pair of twins.
Fig. 6. A complete gait cycle extraction of a $\beta$ signal for a pair of twins.

4. Results and Discussion

Table 1. Average CCR across Two Classification Analyses

<table>
<thead>
<tr>
<th>Classifiers</th>
<th>Average CCR (%) when Classify as a Pair</th>
<th>Average CCR (%) when Classify as an Individual</th>
</tr>
</thead>
<tbody>
<tr>
<td>LDA</td>
<td>76.00</td>
<td>43.75</td>
</tr>
<tr>
<td>3-NN via Euclidean</td>
<td>68.75</td>
<td>65.63</td>
</tr>
<tr>
<td>1-NN via Euclidean</td>
<td>83.33</td>
<td>76.00</td>
</tr>
<tr>
<td>3-NN via City-Block</td>
<td>68.75</td>
<td>65.63</td>
</tr>
<tr>
<td>1-NN via City Block</td>
<td>83.33</td>
<td>76.00</td>
</tr>
</tbody>
</table>

The chosen classifiers in this paper are Linear Discriminant Analysis (LDA) and $k$-nearest neighbour ($k$-NN) classifiers. These are established classifiers that have been performing well for small sample supervised classification problem on earlier research in gait recognition (Huang, 2001) (Yam et. al, 2004).

Before the $\alpha$ and $\beta$ signals are put in a classifier, they are concatenated to become a long feature vector of size 60. There are 12 pairs of identical twins with four videos each; two samples of left to right walking and vice versa, respectively. Thus making up a dataset of size 60 x 96. A supervised classification means the dataset has to be divided into training and test set. The classes for the training data have already been defined earlier on. Therefore, in this paper, these analyses are performed; (1) to classify the sample of the individual twin into his/her own class and (2) to classify the sample of the individual twin into his/her own pair. The former analysis aims to look at the uniqueness of each individual twin. The latter
analysis aims to look into the potential “similarity” of the twins. The average CCR is calculated based on the average classification outcome of cross validations. The results are summarized in Table 1.

From Table 1, the highest CCR of 83.33% comes from the analysis using the $k$-NN classifier with $k = 1$ when classifying the twins as a pair. This analysis is an analysis of a 12-fold cross validation, where the classes are the total number of pairs available in the dataset. With the same classifier, when classifying each twin as a unique individual, the CCR is 76%, which is the highest in for the analysis. In this analysis, the average CCR is calculated from iterating through 24-fold cross validation. Naturally the results of the former analysis across all classifiers are higher than the latter is because the former analysis works on a larger training dataset. Hence, a larger learned samples for the classifier.

Additionally, it is apparent that when using a $1$-NN gives better results than $3$-NN in both analyses. So, this paper investigates further by looking at its data distribution. Clearly the one neighbor is one of the other feature vectors for the individual twin, which are the other videos of the individual. However, when the number of nearest neighbours increases, the performance of the $k$-NN classifier drops. This means that there are overlaps of feature vectors in the classification space, where this requires a nonlinear classifier. This may be seen by the results of the LDA of 76% for the analysis as a pair and 43.75% for the analysis as a unique individual where, it is perhaps difficult to determine a linear decision function.

5. Conclusion and Future Work

This paper has performed two supervised classification analyses on identical twins. The motivation behind this is to find out the ability in using gait as a mean of biometric identification to distinguish between identical twins. The dataset consists of 12 pairs of identical twins. This paper has proposed two analyses, the first analysis is to classify any individual twin in the dataset as a unique pair. Via $1$-NN classifier, this analysis achieved 83.33% CCR, which shows that the gait of identical twins as a pair may be unique. With the same classifier, this paper has shown that an individual twin can be classified correctly with the highest CCR of 76%. This second analysis has been proposed to look into each individual twin in the dataset as a unique individual. However, due to the slightly low performance, when comparing to other small sample literatures on non-twins individual (Yam et al., 2004) (Mohd-Isa, 2005), this paper may have not managed to point to the uniqueness of an individual twin yet. This is perhaps due to the nonlinear nature of the dataset. Future work aims to look into using a different classifier.

References


