Performance Analysis of Time-Distance Gait Parameters under Different Speeds

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Abstract. This paper explores gait recognition for various walking speeds. Normal-constant speed is one of the assumptions being made in many current gait recognition techniques. However, some techniques do not scale well when certain gait conditions such as walking speed varies. We demonstrate the characteristics of time-distance gait parameters, stride length and cadence, with respect to walking speed at the inter- and intra-individual variation levels. The speed normalization or adjustment of gait features are studied and presented in details along with the expected recognition results. Our study of walking speed variations allows us to ascertain systematically the expected recognition-performance of time-distance gait parameters (stride length and cadence). In addition, we show the levels of measurement noise which can be tolerated in measuring these gait features without losing useful identity information.

1 Introduction

In recent years, human identification research has shown many effective techniques to automatically identify or authenticate people based on their unique physiological or behavioral characteristics. Gait as a biometric is appealing because of its unobtrusiveness and information can be observed at a distance. There are numerous computer vision-based applications that need a system that automatically identifies people or at least verifies their claimed identity.

Normal walking conditions such as constant and natural walking speed, no object to carry, level ground walking, etc. are some of the main assumptions made in most current techniques. Many proposed features and techniques will not work well if these conditions do not hold. Even though most of the time gait patterns are repeatable, changes in walking conditions can affect the patterns. There are many factors from our daily walking activity, such as, locomotor speed, stride frequency, walking surfaces, load carrying , etc. that can influence the inter- and intra-individual variations. The understanding of the characteristics of gait patterns under various gait conditions will help improve and scale the techniques in the gait research.

We are particularly interested in patterns of time-distance gait parameters such as stride length and cadence, which are potentially measurable by computer vision techniques, under various speed conditions. However, rather than concentrating on coming up with techniques to recover these parameters, we are more interested in studying various properties of these features themselves especially when walking speed is changing. In particular, if people are allowed to walk at arbitrary speeds,

- Which gait features provide more unique individual characteristics? Does combining them help improve the recognition?
- How do we normalize or map time-distance features across speeds to improve the recognition?
- How much noise can be tolerated in these features, so they still yield reasonable recognition performance?
- How much of the redundancy between these features can be exploited in the presence of noise in the measurement?

In this paper, we present our study of inter- and intra-individual gait pattern variations under different walking speeds among a group of normal people. Since measurements of gait patterns directly from video sequences is still coarse and noisy, we propose to investigate, identify, and quantify the gait variations observed from gait cycles using 3D movement analysis system. Analyzing gait data in this aspect allows (without much concern about measurement noise) us to investigate what types of features contain significant individual characteristics.

2 Related and Previous work

Humans can walk up to 4 m/s [10], but natural transition between walking and running is roughly 2.2 m/s [10, 11]. [13, 12] study the influence of walking speed on gait parameters to find out their *normal* ranges. The results can be used as a reference for comparison with other pathological cases. From a human identification perspective, human gaits are observed in various situations, for examples, side-, frontal-, or arbitrary-views, and indoor versus outdoor scenes [1, 2]. Many features are proposed in the literature for gait recognition tasks including optical flow, joint angles, silhouette, etc. Example works include appearance based approaches where the actual appearance of the motion is characterized [3–5]. Several works extract parameters of body and gait, such as, stride length, cadence, height, joint angles to use in the classification tasks [1, 6, 7]. In [8], they analyze the identity information contained in the lower-body joint-angle trajectories using the data measured with 3D motion capture system.

The study of speed effects in gait recognition has not been emphasized much. There are not many works [6, 14] that exploit the relationship of gait features with respect to walking speeds in their techniques to help deal with walking speed variations of people. In [14], they present a method that focuses on distinguishing normal walking movement from other non-walking movements using low-level stride-based features. In [6], they present a model-based technique that estimates stride length and cadence as gait features and use the linear relationship between stride length and cadence in their recognition step.

3 Speed-control experiment

To quantitatively assess the effects of speed variation on gait parameters during walking movements, we design an experimental setup to gather movement information, which allows people to walk naturally on the ground level floor and at the same time achieve and remain at certain speeds. The details of our experimental setup can be found in our technical report [9]. A motion capture system is also part of our setup because we want to evaluate the efficacy of gait parameters at various speeds where their values can be measured as accurate as possible.

There are 15 subjects (12 males and 3 females) with normal healthy condition participating in this study. For each session, the subjects are required to walk at four different speeds (0.7, 1.0, 1.3, and 1.6 m/s). Three walking trials are captured for each speed. To verify the validity and consistency of the data, each subject is asked to participate in 3 sessions. The second session is arranged right after the first. A third session takes place at least a day later. There are $15*4*3*3 = 540$ walking trials collected from this experiment. For each walking trial, one full walking cycle mostly in the middle of the trial is segmented.

4 Characteristics of time-distance features respect to speed

General parameters specific to gait activity such as time-distance parameters are potentially measurable from images by computer vision techniques. These parameters usually include stride length, cadence, stride time, and speed. Several approaches use these features in their recognition techniques with a normal, constant speed assumption. We argue that when people change their speeds, their gait patterns do change. And it is reasonable to assume people do change their speeds. Therefore, it is necessary to understand the expected performance of these features when used in general speed conditions and how to handle them with respect to speed differences.

Since speed is related directly to stride length, cadence and stride time parameters, our speed-control data allow us to look at these parameters more closely in their characteristics respect to speed. From our speed-control setup with the 3D motion capture system, stride length and stride time can be measured directly from the 3D walking data. *Stride length* is defined as the distance between one heelstrike to the next of the right foot in the walking plane. *Stride time* is computing by dividing the number of data samples of each walk cycle by the sampling rate (120 Hz in our case). *Cadence* (strides/min) is calculated by dividing 60 seconds by a stride time (seconds).

Normally when people increase their walking speeds, both their stride and cadence are adjusted accordingly. It is known that stride length increases monotonically as walking speed increases. In gait recognition, however, we need to know the relationship between these features at the individual level in order to find a way to adjust, normalize, or map features across speeds for the recognition tasks.

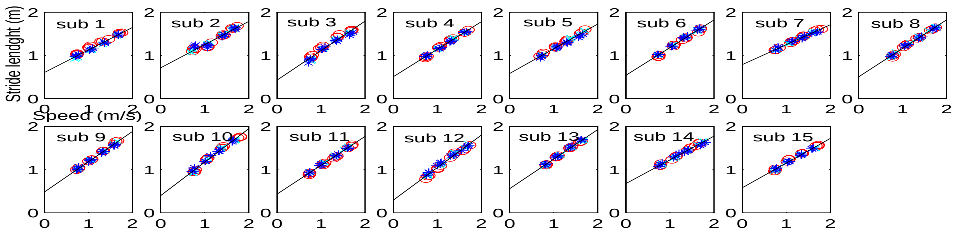

Fig. 1. Linear relationships between stride length and speed of 15 subjects. For each subject, 4*3*3=36 data points are plotted and a mean line is fitted through them.

Figure 1 shows the linearity between stride length and walking speed from all trials of 15 subjects. Moreover, we can see that the fitted mean lines of the subjects have different slopes. Figure 2 *(row (a))* shows all data from 15 subjects (left), the fitted mean lines plotted together give us a better view of the similarities and differences between individuals (middle), and the coefficients (slope and y-intercept) of the 15 lines in the coefficient space (right). One observation about the slopes of the fitted mean lines is that if a person has a narrow stride length at small speeds, he/she has to increase stride length more at the higher speed to be able to cover a certain distance in a certain amount of time. Therefore, the slopes tend to be steeper than the slopes of those who have a wide stride length at small speed. Similar linear relationships can be found also in the cases of *[cadence, speed]* and *[stride length, cadence]* pairs (figure 2 *row (b) and (c)*).

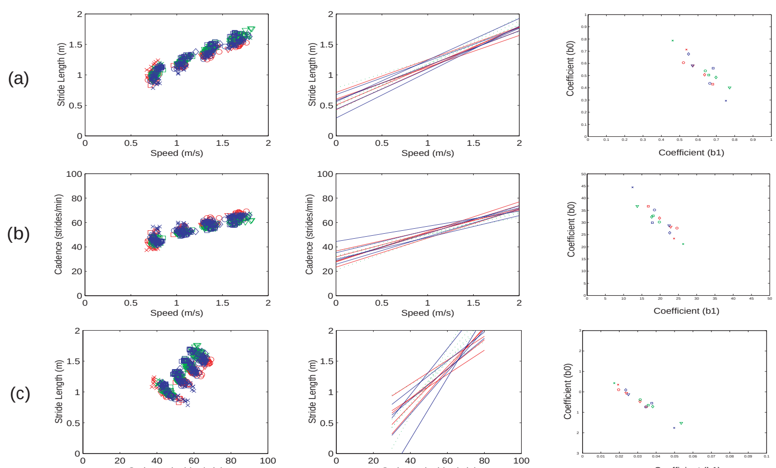

Fig. 2. Row (a), Left: All stride length and cadence data from 15 subjects plotted altogether. Middle: Individual fitted mean lines. Right: Distribution of the coefficients of 15 lines. Row (b) and (c) are the similar plots for [cadence, speed] and [stride length, cadence] pairs.

5 Expected performance of time-distance features

All linear relationships between the features in the previous section hold at the individual level as well as at the group level. In gait applications, if there are several walking examples at different speeds for each individual, the individual fitted mean line can be approximated and used to predict the stride length or cadence of that individual at any speed (within a reasonable range). From the point of view of implementing a gait recognition system, we normally will not have individual slopes to compensate for speed differences. In the following paragraph we compare the use of individual fitted mean lines to the global one (the fitted mean line of the whole group) to see if we can use the global line in the mapping process.

To perform a recognition task across speeds, one way is to normalize or map all data to a particular speed (template speed), and then use pattern recognition techniques to classify them. We used the simple nearest neighbor algorithm with Euclidean distance as measurement criteria. The results are presented in the form of the Cumulative Match Characteristic (CMC) curves, which indicate the probability that the correct match is included in the top n matches.

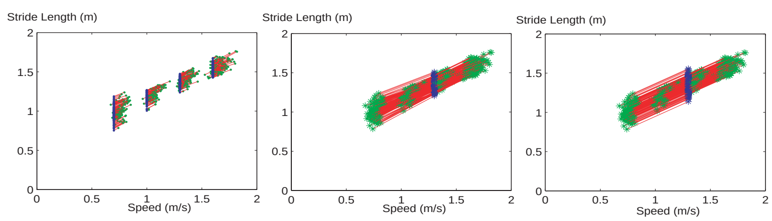

Fig. 3. In the stride length case. Left: map all the data from 4 different speed settings to be at their respective exact speeds. Middle: map all data to 1.3 m/s using the individual mean lines. Right: map data using the global mean line.

Stride length and cadence

Figure 3 (left) shows the analysis of the performance of the stride length feature at a chosen template speed. For example, if the template speed is 0.7 m/s, then we adjust the stride length data captured from each subject at around 0.7 m/s in our experiment to be at exactly the speed at 0.7 m/s using the individual fitted mean lines. In our case, 15(people)*3(trials per suit-up)*3(suit-ups)=135 data points are mapped to the template speed and they are considered a *probe* set. The *gallery* set is constructed by taking the stride length values from the individual fitted mean lines at the template speed (0.7 m/s). Therefore, there are 15 stride length values in the gallery set at any speed representing 15 individuals. Each probe data point is compared against the data in the gallery set using the nearest neighbor algorithm to find the match. To validate the results, we select 4 different speeds as the template speeds for comparison. Figure 4 *(frame (a), solid curves)* shows the CMC curves obtained from using the stride length feature. Their similarities suggest the expected recognition-performance of the feature regardless of any speed.

From the linear relationships in the previous section, if we have the gallery set at one particular speed, and the probe set at other speeds, the recognition would be poor. A normalization is needed to deal with the speed differences. We investigate two mapping techniques, using the individual and global fitted mean lines. Figure 3 (middle and right) shows the mapping process using both methods. We select 1.3 m/s to be the template speed. The gallery set at 1.3 m/s is the same as before, but the probe sets are the data at the speeds 0.7, 1.0, and

1.6 m/s mapped to 1.3 m/s. Figure 4 *(frame (a) dash and dots curves)* represents the CMC curves using both normalization methods. Using the individual fitted mean lines as the mapping tools yields good results (*dash* and *solid* curves are close to each other). Using the global fitted mean lines yields slightly worse performances (especially at the small speed (0.7m/s) where people have more variations in executing their gaits). However, without enough examples of a person to obtain the individual mean line, the global mean line gives a reasonable way for mapping the data across speeds.

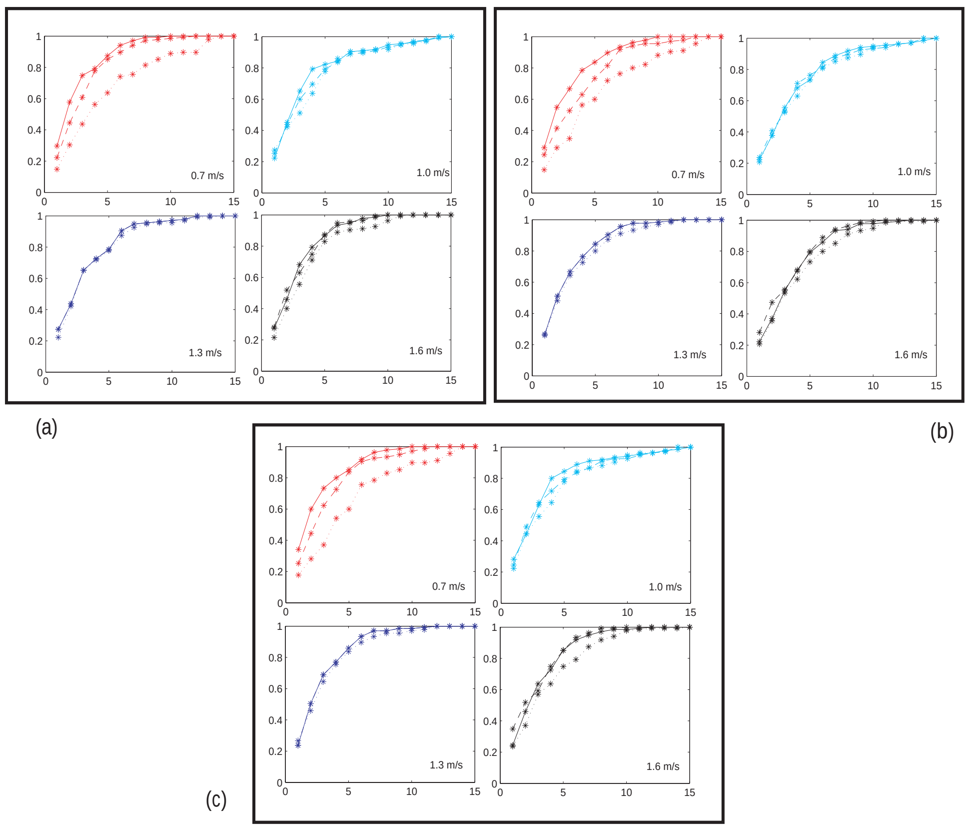

Fig. 4. Frame (a): CMC curves in the stride length case (*Solid*: at a particular speed (no mapping across speeds), *Dash*: with speed adjustment to 1.3 m/s using the individual mean lines, *Dots*: using the global mean line). Frame (b): the cadence case. Frame (c): the case of using both stride length and cadence.

The same protocol is applied to the analysis of cadence feature. The similarities of the CMC curves (figure 4, frame (b), *solid* curves) also suggests the expected recognition-performance of the feature regardless of speed. With the knowledge of the individual fitted mean lines, the mapping process can be done reasonably well. If the individual fitted mean lines are not available, then the global mean line can still be used to help normalize the data closer to its likely value at the template speed (figure 4 frame (b), *dash* and *dots* curves).

The expected performance when using both stride length and cadence together can be seen from the similarities of the curves in figure 4 *(frame (c), solid curves)*. The similar conclusions about the normalization techniques can be observed from the CMC curves in figure 4 *(frame (c), dash and dots curves)*.

There is, however, one interesting observation from our analysis of these expected performances. By considering any particular speed, for example, at 0.7 m/s (top-left), if we plot CMC curves obtained from using only stride length alone, cadence alone, and both features together, we can see that they are not much different from one another (figure 5). This result suggests that in the noise-free measurements, using both features does not yield significantly better recognition performance than using either one alone.

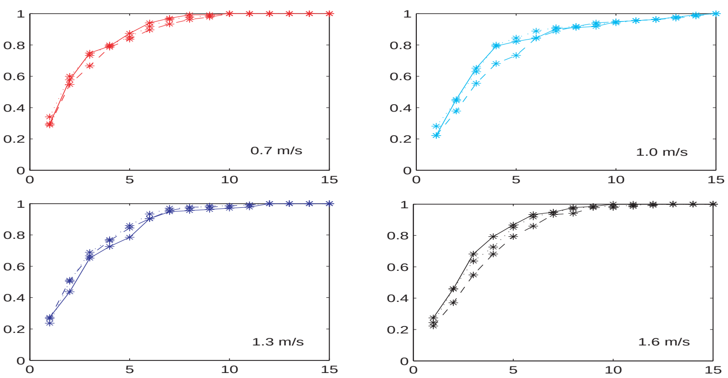

Fig. 5. CMC curves at 4 different speeds (*Solid*: using stride length feature alone, *Dash*: using cadence alone, *Dots*: using both features).

Noise analysis

The data we use in this analysis are 3D motion capture data which are considered to be accurate. This allows us to explore the real values of the features themselves. However, when obtained from images, these features are expected to be coarse and noisy. We want to know how much measurement noise can be tolerated in order to still yield useful recognition performances.

For example, given that a person walks at the speed of exactly 1.3 m/s, but a vision algorithm can measured the stride length with some level of noises. We simulate this situation by taking the data in the probe set at the speed 1.3 m/s and adding random noises which have normal distribution (zero mean and standard deviation ranging from 0 cm to 48 cm). We match this noisy probe set against the gallery set at 1.3 m/s. Then we calculate the CMC curve. For each level of noise, we simulate the results 30 times and then average all the CMC curves. We show the averaged CMC results in figure 6 *(frame (a))* with the noise level incremented by 3 cm in each step. Another simple way to compare these CMC curves is to calculate their area under the curves (right plot). We can see that the more noise in the measurement, the more random the data will be and the CMC curve will be closer to the diagonal line (or the area under the CMC curve will be closer to 0.5). From the plots, we can see that the

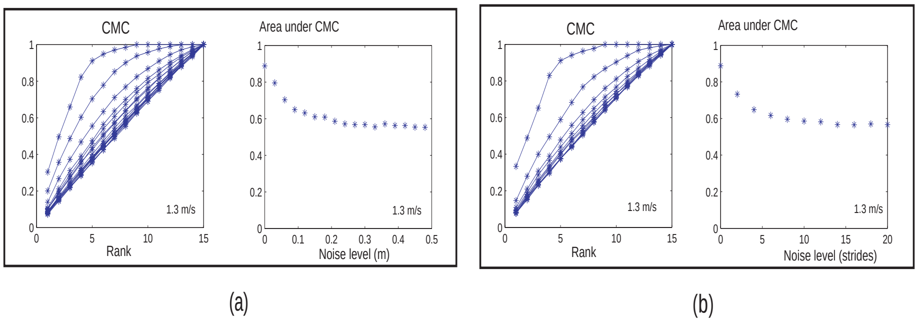

Fig. 6. Frame (a), Left: CMC curves when different levels of noises (from 0-48 cm/s) are added to the stride length measurement at the speed of 1.3 m/s. Right: Area under the CMC curves from the left figure (normalized to be from 0 to 1) plotted according to different levels of noise (0-48 cm/s). Frame (b), in the case of cadence.

stride length feature still yields useful information until the standard deviation of measurement noise is about 9-12 cm. Similar noise analysis of the cadence feature is also shown in figure 6 *(frame (b))*, where The standard deviation of noises added to the original measurements are from 0-20 strides/min.

In the case of noisy measurement, however, knowing both features might be better than knowing one feature alone. Since it is difficult to show the CMC curves when noises are added to both features. Only plots of the area under those CMC curves are shown in figure 7. The more noises included in the measurement, the worse recognition performances reflected in the lower CMC curves. However, in figure 7, (b)-(d) the plots suggest that using both features in the noisy measurements yields better CMC curves than using either one noisy feature alone. Therefore, the redundancy between these two features help the recognition performance in the presence of noise in the measurement.

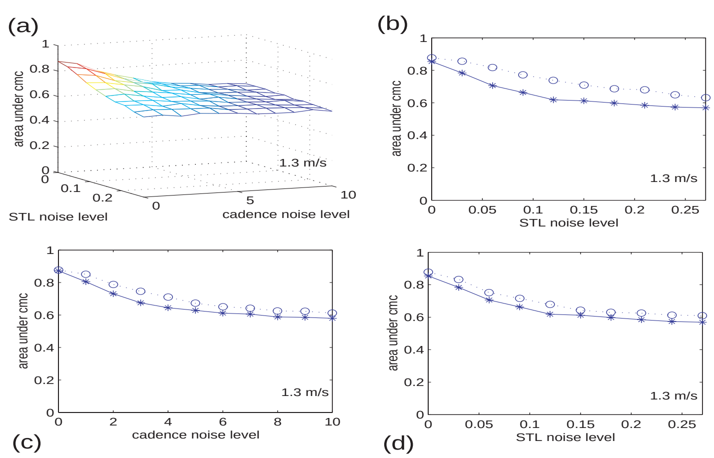

Fig. 7. (a) Plots of area under the CMC curves when noises are added in the measurement of stride length (0-48 cm/s) and cadence (0-20 strides/min). (b) Comparison of the area under the CMC curves between *solid* (using only stride length as the feature alone and noises are added to the measurement) and *dots* (using both features, but noises are only added to the stride length measurement). (c) Similar to *(b)* but both curves represent cadence instead. (d) Similar to *(b)*, *dots* (noises are added to both features which is the diagonal values of the surface in *(a)*).

6 Summary and conclusions

This paper presents the detailed analysis of time-distance gait parameters especially stride length and cadence across walking speeds. We have shown the linear relationships of these features at the levels of the inter- and intra-individual variations and their expected recognition-performance. In dealing with speed variations, we conclude that the normalization using the global mean line is a reasonable thing to do in a general case where individual mean lines are unavailable. We show the levels of measurement noises which can be tolerated in these gait parameters and the redundancy between them that can be exploited in the presence of noise.

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