Pattern Analysis Using Lower Body Human Walking Data to Identify the Gaitprint

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***Abstract*— All people have a fingerprint that is unique to them and persistent throughout life. Similarly, we propose that people have a gaitprint, a persistent walking pattern that contains unique information about an individual. To provide evidence of a unique gaitprint, we aimed to identify individuals based on basic spatiotemporal variables. Healthy young adults were recruited to walk overground on an indoor track at their own pace for four minutes wearing inertial measurement units. A total of 18 trials per participant were completed between two days, one week apart. Four methods of pattern analysis, a) Euclidean distance, b) cosine similarity, c) random forest, and d) support vector machine, were applied to our basic spatiotemporal variables such as step and stride lengths to accurately identify people. Our best accuracy (99.38%) was achieved by the support vector machine and by the top 5 and top 10 most similar trials from cosine similarity. Our results clearly demonstrate a persistent walking pattern with sufficient information about the individual to make them identifiable, suggesting the existence of a gaitprint.**

***Index Terms*— Biometrics, Euclidean distance, Gait recognition, Inertial measurement units (IMUs), Noise, Random forests, Support vector machines (SVM), Variability.**

I. INTRODUCTION

Walking is a fundamental function of the human body and is ubiquitous in daily life. Walking generally entails the same process, such as moving the center of mass over the support leg; however, there is considerable variety in the way that any given person solves this task. The uniqueness implied by that description supports the idea that each person might possess a “gaitprint” in the same way each person has an enduring fingerprint observable across the lifespan. Indeed, one can reliably identify friends and family with limited visual - in the extreme, only auditory - information. For example, in the classic ‘point light walker’ paradigm, reflective markers that are placed on anatomical landmarks of a participant are video recorded during walking [1]–[3]. Otherwise, the room is completely dark such that, when played, the video displays a series of floating white dots on a black background. Days or months later, the same collection of participants are able to recognize each other, and naïve participants can recognize changes in the behavior of an unknown person’s actions [1]–[3]. Anecdotally, people can also identify others based purely on the sounds of their stepping patterns from the variance in their cadence. This ability appears to be supported by literature [4], [5]. Despite those indirect results, the actual question as to whether people exhibit a unique gaitprint remains unanswered. In this manuscript, we contend that the key to discovering a gaitprint rests on the examination of the variability in human movement. Based on that contention, the purpose of this paper is to capitalize on the fundamentals of human movement, and its variability, to produce evidence for unique gaitprints, a collection of gait features that can reliably identify an individual [6]. We hypothesize that principled gait features including movement variability can uncover a unique gaitprint for each person [7]. To probe this hypothesis, we draw from numerous methods to accurately identify individuals with quantitative descriptions of lower-body kinematics [1], [8]. We combine simple pattern recognition techniques with detailed, multi-day measurements of gait features to identify each individual's gaitprint.

A. Human Movement and the Gaitprint

Many human movements, like walking, entail many repetitive cycles. Despite the cyclic nature of gait, there is considerable variability from one stride to the next. Some steps are short; some are long. Some steps are slow; some are fast. The variability across cycles was conventionally interpreted as a representation of uncontrolled noise and/or error to be removed [7]. However, a large amount of research has revealed that the variability underlying human movement and signals is not merely uncontrolled noise nor error [7], [9]–[11]. Based on these findings, here we propose a novel hypothesis that the variability observed over repetitive gait cycles is fundamental to the unique strategies people employ to walk about the world. That is, variability reflects the unique walking solutions learned over the course of development. Hence, variability encapsulates the developmental history of an individual and is the source of

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Additional figures, data, and code can be found in the supplementary material.

features that ultimately allow identification from gait features.

More formally, we define a gaitprint as a persistent walking pattern that contains unique information about an individual. As an analogy, a fingerprint contains ridges with swirls and arches of varying widths that ultimately lead to changes in ridge placement, orientation, or bifurcations [6]. Microclimates within the womb detail the makeup of a fetus' fingerprint within an environment that will never be the same [6]. Much like the ridges of finger pads providing meaningful information about the person, a certain set of gait characteristics including kinematics and spatiotemporal variables directly influence gait. Distinct joint trajectories, stride lengths, and other parameters, are the 'ridges' of gait that provide distinct information about walkers. These 'ridges' ultimately form a toolbox from which we can selectively use gait features to distinguish between people using pattern recognition.

B. Gait as a Biometric

The use of gait features for biometrics – identification based on bodily motions and features – is not new [12], [13]. Several previous studies have attempted to identify people based on their gait [14]–[16]. Some other studies included silhouette-based identification by reducing video frames of a person into a silhouette [17]–[19]. Characteristics of the silhouette such as its size and shape can be compared between people for identification [18]–[21]. Another method included kinematics-based identification by directly measuring, or estimating, limb kinematics for comparison [15], [22]–[25]. However, silhouette and kinematics-based identification methods share common limitations. Silhouette-based identification may be affected by camera perspective, shadows, or background scenes that obscure or completely occlude the participant walking [12], [13], [19]. In addition, the burden lies upon the participant to come into the laboratory to be equipped with full body sensors for kinematic-based identification. Specific to silhouette identification, appearances can change due to various factors like clothing, therefore reducing person identification accuracy across days [19], [26]. There are also limitations specific to kinematic-based identification. For example, previous studies have used abstract and complex data transformations or use thousands of identifiable features that are accurate, but may take a long time to calculate or are not generalizable [15], [27]. These studies approach gait identification by evaluating kinematics between high and low dimensions rather than identification based on raw kinematics. Their principal component and three-dimensional transformations may be effective but lose their intuitiveness and clarity. One such study achieved 100% identification accuracy [27]. However, this achievement is facilitated by training and testing within trials, rather than training and testing between trials. Perfect identification accuracy is not unexpected since kinematic measurements within the same trial are likely to be correlated and are self-similar across scales [28]–[31]. The lack of identification between trials also implies an inability to correctly identify discontinuous walking bouts, which would be more realistic for on-the-fly identification across hours, days, months, or even years. In addition, computation times may be too slow for near-real-time person identification during time-sensitive situations. Therefore, the goal of perfect identification accuracy from simple and easy to compute variables between walking trials must still be achieved.

For other kinematic related studies, their limitations may have led to a range of success between 42 to 99.71% identification accuracy [14], [15], [23]–[25], [32], [33]. Across this range, perfect identification accuracy may have been prevented by random chance of assignment to gallery and probe, limitations of the identification methods, or limitations of the variable selections themselves. Some studies directly address and ameliorate the issues of reduced identification ability occurring from sources such as inconsistent camera angles [22], [34]. Our team's approach focused on treating all these above-mentioned limitations to progress pattern recognition towards perfect accuracy using a simple framework.

C. Advantages

The present work may be distinguished by a focus on sensors that record human movement, regardless of viewpoint, and a focus on long, curvilinear walking paths within an environment that is familiar to participants. Inertial measurement units (IMUs) are portable and do not rely on a fixed camera placement, predefined calibration space, or predefined capture volume. The IMUs are especially useful because they allow our participants to walk around a looping indoor track with variable lighting, noise, and foot traffic. These benefits are seen as an improvement because we do not rely on treadmills that are known to affect gait [35]–[37]. We also focus on basic lower body gait descriptors that are computationally efficient and easily described to a lay person. Stride lengths and step widths can be recognized in real time and are intuitive to interpret and describe. For example, a close family friend might have a distinctly large step width that makes them easily recognizable from a distance. Our simple biomechanical approach is in stark contrast to more abstract means of pattern recognition [15], [27]. In addition, only a few studies use a limited number of kinematic measures of variability, whereas one-third of our gait features are about variability [14], [25], [38], [39]. Finally, we successfully tackle the challenge of multi-day person identification. High identification accuracy over two data collection sessions, separated by one week, provides evidence that gait characteristics are a useful tool for identification between days. Those advantages serve as the foundation for our pattern recognition study reported here.

D. Purpose

The purpose of this paper is to determine if gait is unique to each person. Overall, we hypothesize that the way each person walks reveals subtle information about their identity.

Fig. 1. (a) Indoor track where overground walking data was collected. (b&c) Anterior and posterior views of the Noraxon IMU setup.

II. METHODS

A. Data Acquisition

Thirty healthy young adults between the ages 19-35 were sampled from the NONAN GaitPrint dataset [40]. Between 2 days, participants completed 18, 4-minute, self-paced overground walking trials (n = 540 total trials) on a 200-meter indoor track while wearing 16 Noraxon Ultium Motion inertial measurement units (IMUs) recording at 200Hz (Fig. 1). Participants were also given a short, optional break after every 3 trials. A total of 74 variables were calculated including bilateral spatiotemporal variables consisting of distance traveled, average speed, cadence, stride and step lengths, widths, and times, supplemented by the percentage of stance, swing, and support phases (see Supplementary Material and Supplementary Fig. 4-9). Bilateral lower body joint angles (hip, knee, ankle) were used to calculate their mean and standard deviations of peak flexion, extension, range of motion, and velocity. All spatiotemporal calculations were completed in Matlab version R2022b and the following data handling and identification models were completed using Rstudio version 4.2.2 [41]–[44].

B. Data Handling

We used three methods to split our data into galleries and probes (Fig. 2). Split 1 (70/30) included a random 70%/30% split of all trials to be placed in the gallery and probe, respectively. That meant a total of 378 walking trials were used as a reference for the remaining 162 probe trials. Split 2 (referred to henceforth as Day 1) used all trials from day 1 as the gallery set, and the day 2 trials were used as the probe. That is, 270 trials were used as a reference for the remaining 270 probe trials. Split 3 (now referred to as Trial 1) used the very first trial from day 1 as the gallery set, and the remaining 17 trials per participant were used as the probe. A total of 30 walking trials were used as a reference for the remaining 510 probe trials.

C. Identification Methods

Gait identification was performed using 4 common methods found in the literature: Euclidean distance (ED), cosine similarity (CS), random forest (RF), and support vector machine (SVM) classifiers [12], [21], [45]–[49]. Those methods can further be divided into two categories, distance based identification (DBI) and model-based identification (MBI). Both categories used all 74 kinematic variables segmented by our three methods of splitting trials into galleries and probes. Regarding DBI, ED was calculated simply as the L2 norm between two vectors (kinematic variables) and CS was calculated as the normalized dot product between two vectors (kinematic variables). We also present DBI accuracy as Rank 1, Rank 5, and Rank 10 (Table 1 and Fig. 3). Each rank represents the most similar, as well as a pool of the 5 and 10 most similar comparisons, to make a true or false decision about the correct attribution of each probe trial to a gallery trial, respectively. Regarding MBI, when applying RF and SVM, we used public R packages including random Forest, stats, and e1071 along with custom functions found in our supplementary material [48]–[50]. Our two MBI methods only contain Rank 1 accuracy.

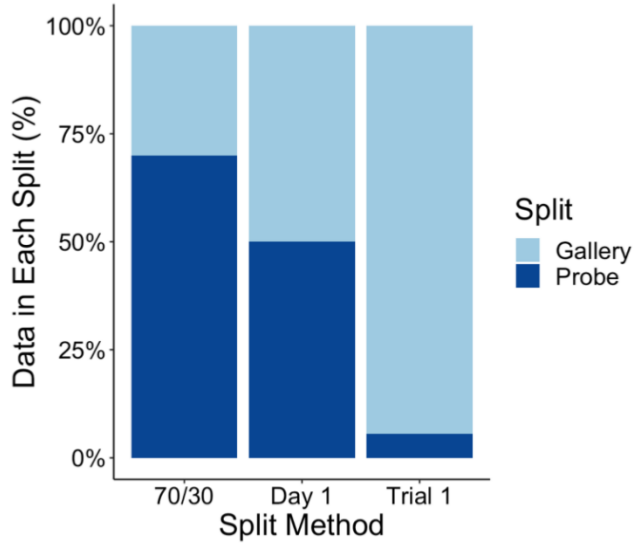

Fig. 2. Visualization of the amount of data split into a probe and gallery for three split methods. 70/30 data is split as 70% gallery and 30% probe. Day 1 data is split as 50% gallery and probe. Trial 1 data is split as 5.88% gallery and 94.12% probe.

III. RESULTS

Overall, subject identification was remarkably accurate considering the intended simplicity of our approach (Table 1 and Fig. 3). Out of the 24 identification combinations noted in Table 1, only 4 were below 70% accuracy, 7 were between 70-90% accuracy, and 13 were above 90% accuracy. Of the 13 results resting above 90% accuracy, 5 reached at least 98% accuracy. Unsurprisingly, accuracy decreases greatly as the size of our gallery trials decreases, more so when using DBI compared to MBI. In terms of the 70/30 split, the best approach was CS Rank 5, Rank 10, and SVM, followed by ED rank 5 and Rank 10, RF, CS Rank 1, and finally ED Rank 1. In terms of the Day 1 split, the best approach was CS Rank 10 and RF, followed by SVM, ED Rank 10, CS Rank 5, ED Rank 5, CS Rank 1, and ED Rank 1. In terms of the smallest gallery from Trial 1, the best approach was CS Rank 10, followed by CS Rank 5, SVM, ED Rank 10, RF, ED Rank 5, ED Rank 10, and

Table 1. Correct identification accuracy per data split for Euclidean distance (ED), cosine similarity (CS) random forest (RF) and support vector machine learning (SVM).

Split	ED Rank 1	ED Rank 5	ED Rank 10	CS Rank 1	CS Rank 5	CS Rank 10	RF	SVM
70/30	93.21%	98.15%	98.15%	93.83%	99.38%	99.38%	96.91%	99.38%
Day 1	68.89%	88.52%	92.59%	80.37%	91.48%	95.93%	95.93%	94.74%
Trial 1	46.27%	65.29%	77.84%	60.78%	84.11%	88.43%	75.88%	82.55%

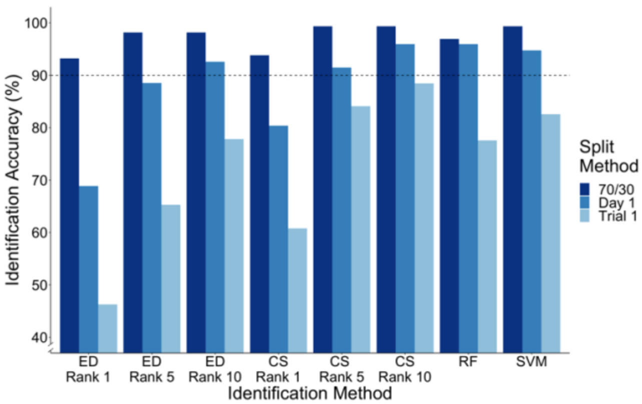

Fig. 3. Correct identification accuracy per data split for Euclidean distance (ED), cosine similarity (CS) random forest (RF) and support vector machine learning (SVM). Dashed horizontal line clarifies 90% accuracy.

ED Rank 1. ED Rank 1 always had the worst performance compared to all other DBI and MBI approaches.

IV. Discussion

In this study, we demonstrated that relatively simple methods of data identification combined with basic gait descriptors effectively distinguishing between individuals. We applied DBI and MBI pattern recognition to spatiotemporal characteristics derived from thirty healthy young adults walking on an indoor track wearing IMUs. Cosine similarity was the better of the two DBI methods reaching 99.38% accuracy when using Rank 5 & 10. Furthermore, our results showed near-perfect accuracy (99.38%) when the SVM classifier was trained on 70% of the data and probed with the remaining 30%. As we reduced the size of our gallery set, identification accuracy decreased, but MBI approaches proved more robust in handling such reductions.

A. Comparisons to Previous Literature

Our study's results are consistent with or surpass previous literature focusing on identifying individuals based on walking features. We outperformed silhouette-based identification in some cases [17], [19], [21], [51]–[53]. Compared to a Hidden Markov Model, Trial 1 MBI performed better than all but four of twelve experimental probes [51]. In addition, accurate silhouette identification deteriorated as the probe viewing angle becomes more unlike the gallery angle [17], [20]. Viewing angle is an issue avoided by using full body motion capture in our study. The viewing angle issue can also occur using markerless kinematics-based identification [22]. We also observed robust identification across days, which can plague silhouette identification due to changes in clothing. One paper collected gait data four times over two months and achieved a best Rank 1 performance of 63%, a value lower than all our Day 1 metrics [21]. In addition, six of eight of our methods were better than their best top 5% performance (88%) as well [21].

A more appropriate comparison to previous literature includes our ability to exceed the expected accuracy of at least 70% compared to studies using similar kinematic variables [14], [22]–[25], [32]. For example, one study applied joint angle trajectories with ED on two datasets to reach 73% and 42% accuracy [23]. The former result is surpassed by our ED Rank 1 at the 70/30 split (93.21%) and the latter is surpassed by our Day 1 (68.89%) and Trial 1 (46.27%) ED Rank 1 accuracy. Another study used 41 lower body features to achieve 88.78% accuracy using SVM, only higher than our Trial 1 SVM (82.55%) but not Day 1 (94.74%) or 70/30 SVM (99.38%) [14]. Finally, our results were comparable to two studies with more complex data manipulations and many more variables that achieved a very high accuracy of at least 99.5% [15], [27]. We further emphasize that our model is more generalizable because we use an intuitive approach that remains grounded on direct kinematic measurements and potentially quicker to compute through basic gait features. In addition, the intuitiveness of this paper lends itself to support the peculiar ability to recognize friends and family by their gait at a far enough distance where facial features, clothing, or clear vision may be unreliable.

As anticipated, identification becomes more challenging with a smaller gallery. Nevertheless, even with less than 6% of our data used for gallery (Trial 1), we achieved over 80% accuracy using CS and SVM, which is remarkable. Splitting our data in half (Day 1), all but one method was at least 80% accurate. Additionally, our findings showed excellent accuracy (over 90%) when using a gallery from the first day's data (Day 1) and probing on the second day, addressing the challenges of multi-day identification [19], [21]. However, it is worth noting that our study investigated gait with a 7-day gap, while other studies spanned months or even one year, potentially allowing for more significant natural gait changes [19], [21], [54]. Inter-day identification suggests that gait is inherently variable but still contains consistent characteristics or a unique "gaitprint”.

B. Limitations

Consistent with the limitations of other identification methods that require a designated space for equipping participants and capturing data (i.e., fingerprinting), we also required the participant to come into the lab to wear equipment that is typically not available to the public. We hope, however, that the development of markerless motion capture can be used to provide detailed accounts of the entire body as seen in this report in a more covert manner. Advancements in markerless motion capture technology that can calculate reliable and accurate gait kinematics will permit highly accurate, yet surreptitious person identification based on how we walk. Coupled with the present study's ability to accurately detect individuals based on gait, we will then be able to knock out two main problems of gait identification. The first issue is quantifying gait in a natural environment without instrumentation and the second issue is the currently worked on challenge of extracting gait kinematics due to the limitations of videography [12], [22], [34].

C. Future Directions

Future studies in gait identification aim to achieve perfect identification accuracy by further refining the motion capture and kinematic-based perspective. While this paper focused on linear measures (capturing the central tendency and the magnitude of variation) of angular and spatiotemporal gait features as proof of concept, there could be room for improvement by incorporating additional variables into the identification parameters. Further refinement may also be achieved by swapping out, or selecting, the most predictive gait characteristics for identification. For example, the weakest four 70/30 SVM predictors (% Stance and % Swing) could be replaced with other gait descriptors or removed entirely. This may lead to a more accurate set of gait measures and potentially increase precision, although it would provide little novelty.

Currently, we are exploring the value of incorporating nonlinear measures (capturing the temporal structure of variation) as additional gait features considering the importance of movement variability. However, some nonlinear analysis methods require a large number of strides for accurate results, which are not feasible in stationary camera settings where the pedestrian may walk in and out of the capture space. Nonetheless, related work from our lab provided evidence supporting the replacement of certain nonlinear analyses with reliable results using as few as 64 data points [30]. While this reduction still represents a significant number of strides depending on the identification space and population, we anticipate that nonlinear analyses will become useful predictors for identifying individuals in the near future [55]. Specifically, the particular structure of trial-to-trial variability may indicate individual uniqueness and provide insights into subtle coordination changes that reveal a person's identity. Our future capitalization on more nuanced measures of gait variability, rather than standard deviations, is expected to improve identification accuracy. The importance of nonlinear identifiers is supported by literature demonstrating their usefulness when investigating gait in different populations [7], [56]–[58]. Furthermore, a wider range of machine learning classifiers is being investigated, and the importance of variables in machine learning outcomes is being studied at present.

D. Significance

Our results clearly suggested that a person's identity is indeed linked to gait patterns during overground walking. Our predictions ultimately rested on the primacy of movement variability in forming unique gaitprints. Consistent with that idea, variability measures were consistently among the most important parameters for MBI. Even at the most basic level of measurable variability, person identification has been strengthened. In addition, the method outlined here is computationally efficient. Because we chose easily conceptualized gait descriptors instead of complex transformations of our data, our 74 variables were quickly calculated and were ready for use in DBI and MBI applications. An efficient research team should be able to execute a quick pipeline (i.e., equip the participant with IMUs, calibrate the sensors, collect a short walking trial, export the data, apply automated scripts) for registration within 10-15 minutes.

In addition, our approach stands out from several others by virtue of a few secondary topics that are worth mentioning. First, the use of IMUs eliminated the challenges of camera viewpoint, clothing type, lens distortions, or shadows that could hinder identification performance. Second, our study benefited from a less constrained walking path. While many gait identification studies focused on capturing a few strides along a short, straight path or treadmill, we collected data from overground walking on an indoor track, encompassing different distances, curves, walking speeds, and number of strides [14], [15], [21]–[23], [45], [54], [59], [60]. Finally, our basic spatiotemporal variables can be visually described without difficulty, highlighting the observable differences that make two or more individuals distinguishable based on gait metrics.

V. Conclusion

Our study provided evidence that gait, and its variability, can serve as a distinguishing feature in humans. With four simple identification algorithms, we presented an easily understandable method for differentiating between individuals. We achieved near-perfect identification accuracy in some cases, but also observed deteriorating accuracy as our gallery size decreased. In the future, nonlinear analysis methods and other machine learning techniques are expected to bridge the gap between current error rates and achieving 100% human identification accuracy.

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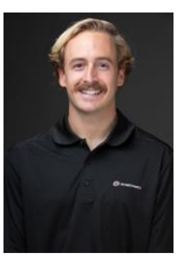

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