Human Recognition via Gait Identification Using Accelerometer Gyro Forces

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ABSTRACT

Many applications, both cooperative and hostile, require the ability to identify humans. This paper proposes a method that exploits the biometric property of human gait to identify people. A single sensor composed of an accelerometer and gyroscope is used to record gait characteristics. Using a Direct Form II Transpose, gait cycles are extracted and compressed to their characteristic features. Using simple classifiers on these feature vectors, this approach achieves 95% accuracy in classifying gait cycles to individuals. This model-driven approach uniquely exploits the physics of human gait through the use of gyroscope forces and proves its viability for smart environment applications.

1. INTRODUCTION

Many applications, both cooperative and hostile, require the ability to identify people. Biometrics are popular for identifying people because they are difficult to fake and easily produced. Biometrics refer to the various intrinsic or physical signatures people produce that can be used to uniquely identify them. Some examples of biometrics are fingerprints, eye scans and voice. This project focuses on the biometric of human gait and attempts to use a person's gait to identify him or her. Human sensing (ie detection or identification), and, in more security-based applications, authentication often use biometrics. Sensing and sensor networks are valuable for many reasons, perhaps the simplest of which is the ability to proactively perform some action based upon the existence of some condition in the observed environment. The work of this project falls within this notion of the "smart environment". Although there exist countless situations for smart environment systems, a simple scenario adequately motivates this project.

Consider a human subject who enters an indoor personal space, such as a bedroom or an office. This person has enabled the "smart space" to observe his/her movements so that the environment can perform actions based on previously determined preferences. Furthermore, the user allows the system to record and learn behavioral patterns in order to improve future system performance. The goal of the system is to leverage the ability to identify the person with previously learned knowledge about the person in order to provide personalized, enhanced services. Examples of such services might be automatic account log-in or other content-based preferences. Beyond these, more physical services might exist in the form of temperature control or window blind adjustment. In order to enable the Enhanced Service Area system, there must be a means for sensing and identifying a human subject "on the fly"; proactively and unobtrusively.

This paper proposes a new approach that uses a single device to measure a person's gait and form a biometric signature based on accelerometer and gyroscope forces. This approach has several unique characteristics that can be either advantages or disadvantages, depending on the nature of the application:

- It uses an accelerometer and a gyroscope, both of which are increasingly embedded in cellular phones.
- The device is small enough to fit in a pocket.
- The device communicates via Bluetooth with a remote station, which carries out the computation.
- The device must be carried “on the person” of the subject (generally in the pocket of the pants).

For the purpose of this paper, the Enhanced Service Area application is the targeted application. Thus, the unique attributes of this approach are advantages. However, it is important to note, again, that the use of biometrics and gait is specific to the nature of the application. This work's approach is not ideal for every biometric application.

This paper proceeds in the following section to describe the nature of human gait and how related work has targeted the anatomy of the human walk to form a biometric signature. Section 3 presents the hardware used and the data it produces, which reflects the characteristics of the human walk. The following section shows how the gait signature is produced using the accelerometer and gyroscope data. Section 5 describes the experimentation and evaluation of the approach in its ability to identify (and track) human subjects. Finally, there is a discussion on the limitations of the approach, as well as a deeper look into the potential applications and future work.

2. RELATED WORK AND HUMAN GAIT

Humans produce many biometric signatures, and the focus of this work is on the biometric properties of human gait. There are several approaches to measuring and leveraging a person's gait characteristics and each has its strengths and weaknesses. Fundamentally, an approach's success is determined by how well it captures the underlying anatomy of a person's gait.

2.1 Related Work for Human Gait

Perhaps the first and initially most popular mechanism for measuring gait was computer vision. One vision approach [2] proved to be practical for tracking people in large, open spaces if cameras can be placed high above the area. Another project uses Markov models [1] to sequence the various postures of a person while walking. Computer vision has also been used for people counting systems [12] [13]. The vision approaches are generally limited by the requirement for a specific camera vantage point or other physical attribute. Thus, in cases where the vision requirements cannot be met, other approaches are more pertinent.

One such method utilizes continuous wave radar [10]. The strength of the wave radar approach is in determining the presence or absence of humans. The work in this paper focuses a step further on how to identify specific people after the detection of a person has occurred. Accelerometers are a second non-vision method. These types of projects are most closely related to the work described in this paper, with some notable differences.

Many related projects [3][4][11][9] use accelerometers to identify a person based on gait. All but one [4] used accelerometers attached to the person either at the leg or the small of the back. Our work differs from these methods in that the accelerometer is placed in the subject's trouser's pocket, just as Gafurov [4] does. In this way, the research of this project is best compared in one sense to Gafurov's [4] because the physical location of the sensor is most similar. However, all these approaches, including Gafurov's [4], only use accelerometer data, not gyroscope data. It is our belief that we are the first to use gyroscope forces to identify human gait.

Lastly, every biometric method is susceptible to different attacks, and the nature of the attack also plays a role in deciding which biometric signature should be used [5]. Ultimately, the environment and requirements of the application will determine the method used.

2.2 Anatomy of Human Gait

Human gait is periodic movement. The period within walking is called the *gait cycle*. A gait cycle is composed of one right leg step and one left leg step. An example gait cycle is shown in Figure 1.

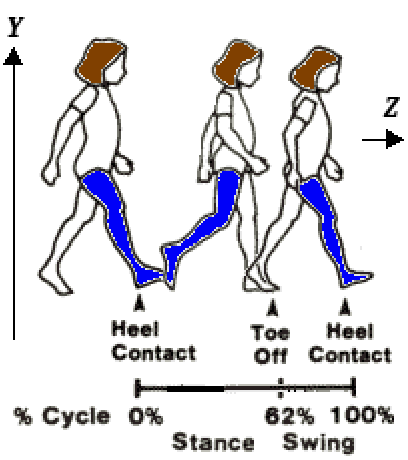

Figure 1. A Gait Cycle [7] (x axis not shown)

Figure 1 shows the y and z directional forces. The x directional force is the left/right axis that goes straight out through the figure. Even when walking in a straight line, a person exerts a slight left/right force. A novelty of this work is the use of a gyroscope to measure the rate of change of the angles about the three axes. The x *gyro* force is the rate of change around the x axis; y gyro force about the y axis and z gyro force about the z axis. Although an accelerometer can be orientated in any way, the orientation throughout this work is exactly as described in Figure 1 and this paragraph. Together, the accelerometer and gyroscope produce six values at any one instant in time (hardware discussed later).

Each gait cycle contains the unique characteristics of a person's walk, and these unique attributes compose the gait *signature*. In order to robustly identify a person's gait signature, there must be a method for extracting gait cycles from a continuous signal of walking data.

3. PERIODICITY

A gait cycle is the smallest repeating unit in the signal produced by the accelerometer/gyroscope. The goal is to take a signal of walking data, identify *x* periods from that signal, where *x* is proportional to time, and then extract the most important features of the period and store the feature vector as one example for the given test subject. Then, an algorithm trains on the test examples and predicts a person based on a given gait cycle. Given the orientation and axes defined in Section 2.2, our accelerometer/gyroscope combination device should produce six data points for any single point in time.

3.1 Hardware

The accelerometer/gyroscope combination device used in this work is the Nintendo Wii Remote (provides accelerometer) used in conjunction with the Nintendo Wii Motion Plus attachment (provides gyroscope). When joined together, the single device measures roughly 7.5” x 1.5” x 1.5”. From now on, this combination device is referred to as simply, the remote. Approximately half of the remote fits easily into most trouser pockets, and in many testing cases, the entire remote fit into the pocket. The remote operates at 50Hz,with a sampling rate upper bound of 100 measurements per second (Nyquist rate).

The remote uses Bluetooth wireless technology to transmit the accelerometer and gyroscope data. A computer with a Bluetooth connection (or usb dongle) records the transmitted data for processing. An example of the remote output for the six degrees of motion, as captured by a computer over Bluetooth, appears in Table 1. Note: the data is in raw units.

Table 1. Accelerometer and Gyroscope Values

time	x	y	z	xg	yg	zg
1258169782.338	121	145	118	7928	7980	7898
1258169782.348	121	145	118	7929	7989	7894
1258169782.358	121	145	118	7934	7983	7850

3.2 Extracting Periods

The average walking speed of a person is roughly one gait cycle per second, but due to the variance in an individual's walk, the length of a gait cycle can change, even in consecutive cycles. Therefore, an identification system needs a more robust method for finding the period, one that is not related to time. Recall the six degrees of freedom and that for any moment in time, there exists six measurement values. Also recall that a person moves vertically up and down while walking. It is this vertical up and down movement, along the previously defined y axis, that enables the period to be measured. With a single accelerometer, the y axis shows a clear repeating pattern from which the period can be extracted. Figure 2 shows the initial y acceleration force and the transformed signal from which gait cycles are calculated.

The approach uses a "Direct Form II Transpose" filter with a Gaussian window of 150 points and a standard deviation of three, which is equivalent to a three second filter because the remote operates at 50Hz. Each local maximum in the filtered signal corresponds to the start of a new gait cycle (the data point immediately prior to the local maximum is the end of the previous period). Note: the time points of the filtered signal are shifted from the corresponding force in the raw signal.

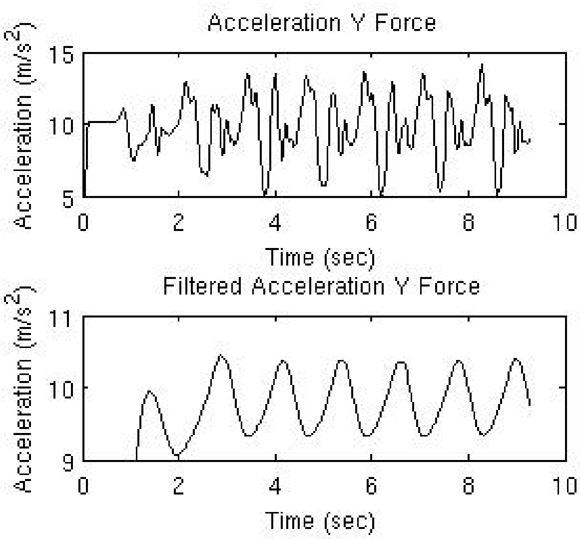

Figure 2. Raw vs. Filtered Y Acceleration

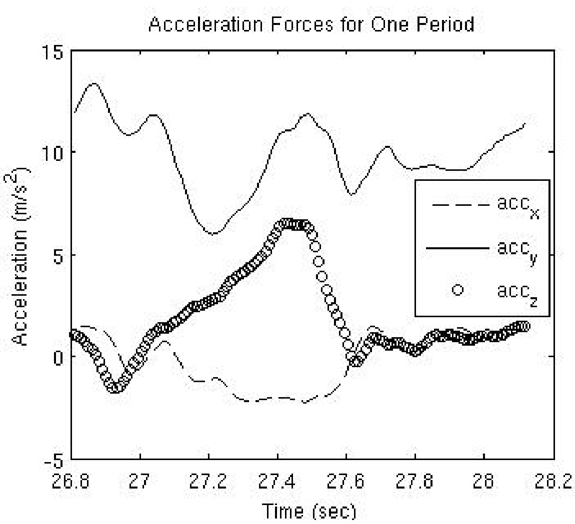

Figure 3. Acceleration Forces for One Period

Related work [4] shows that actual walking registers a force above 1.3g (~ 12.74 m/s^2), therefore, the gait cycles are only calculated after the y acceleration force has exceeded 12.74 m/s^2. This eliminates errors in the filtered signal due to the subject starting from a stationary position. This can also be used to detect when a person is standing versus walking. The filtered signal for Figure 2 shows approximately five gait cycles were present in the unfiltered signal.

Figure 3 shows the x, y and z acceleration forces for one of those gait cycles. The filtered y acceleration signal is used to find the first and last indices in the raw signal that correspond to the start and end of the individual gait cycles. Recall that the remote measures all six degrees of force at the same time. Due to this, the indices produced by the filtered y acceleration signal can be used to demarcate the gait cycle for *each* of the six signals (not just the y acceleration signal). Therefore, six vectors of the same length represent a single period. The average period length in experimentation was approximately 100 data points, which equals a 600 element feature vector. This feature vector represents the gait data output for one period and contains the gait signature of the particular individual. In order to scalably and robustly identify people based on their gait signatures it is necessary to reduce this vector to its most characteristic components.

4. GAIT SIGNATURE

Each extracted period contains six force vectors of equal length. In the Enhanced Services Area system, the goal is to identify a person as quickly and accurately as possible. Therefore, the optimal feature vector is one that contains as little data as possible without losing any discriminative information. In order to find this optimal feature vector, it is important to return again to the anatomy of the human gait.

4.1 Mapping Gait Physics to Input Data Signals

The human gait has inherent attributes that are roughly present in most humans, though the degree of these attributes vary greatly. It is this variation that we hope to capture in our feature vector. While walking, the hips have approximately 30 degrees of flexion and 10 degrees of hyper-extension *around* the x axis (the legs follow this flexion and hyper-extension of the hips). On average, the hips also demonstrate 5 degrees of abduction and 5 degrees of adduction *along* the x axis (again, the legs follow this movement in the hips). Lastly, the hips exert 5 degrees of medial rotation and 5 degrees of lateral rotation *around* the y axis. These values are described in detail in [8]. Figure 4 shows these directional forces.

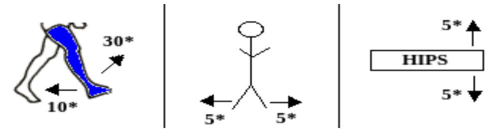

Figure 4. Directional Forces in Walking

Obviously, the optimal feature vector should exploit the variation in these characteristics. Recall that the x axis runs through the hips from the right to the left, and therefore the rotation *around* the x axis corresponds to the gyroscope x force. Therefore, the swing of the legs, which follow the hips, is directly correlated to the gyroscope x force value. The abduction and adduction of the hips, and in turn, the legs, is best measured using the x acceleration force value because it is a force *along* the x axis. Lastly, the rotation of the hips is a rotation *around* the y axis, and therefore the gyroscope y force value best corresponds to the rotation of the hips. Because this project utilizes a single remote, the force values themselves will be periodic and stronger for the leg along which the remote is carried. Using this mapping of the physics of human gait to the measurement data available, we are able to construct our optimal feature vector to describe gait cycles.

4.2 The Feature Vector

Given the above analysis, we investigated if there were visible differences in the gyroscope and acceleration data between two people. For this test, we recorded the remote output data for two test trials. In the first, the subject walked for roughly ten minutes through a building and across a courtyard before turning around. In the second, a different subject walked in a straight line for approximately 1 minute, then turned around and walked another straight line to the starting point. Both subjects were male and of similar height and weight. The main difference was in the duration of the walking sample. For this experiment, the periods were extracted, normalized and plotted on top of each other, to produce one graph for the entire walk. For each subject, six graphs were produced. Figure 5 presents the y gyroscope graph for each subject.

In Figure 5, it is evident that although both y gyroscope periods follow a similar trajectory, the timing and intensity of the inflection points are measurably different. Recall that one subject walked nearly four times as long as the other subject and produced many more periods. Also note that there exist a few periods that are extremely different from the norm for each subject. This is most likely due to the fact that both subjects turned 180 degrees in the middle of their walk. The outliers for an extended walking sample could easily be removed by a rule that eliminates a certain percentage of the least similar periods. Throughout this research it was noted that roughly four periods in each walking sample were outliers. These outliers are left in throughout the work in this project in order to simulate the real-life situation in the Enhanced Service Area system.

The x gyroscope demonstrated similar properties to the y gyroscope. Therefore, the feature vector would include properties from both these signals. Obviously, including the entire signal is both unnecessary and impractical, so each signal was re-sampled at six points and these values were stored in the feature vector. Many different types of properties were investigated such as higher and lower re-sampling rates, as well as statistical results for inflection points and local and global extrema. The re-sampling at six points showed no considerable loss of specificity and is obviously much simpler and smaller.

The x acceleration proved to be a different case altogether. Figure 6 shows the plot comparison for the x acceleration value for the same two walking subjects as Figure 5. Just as it was in the Y Gyroscope signal, the trajectories are similar and the inflections dissimilar.

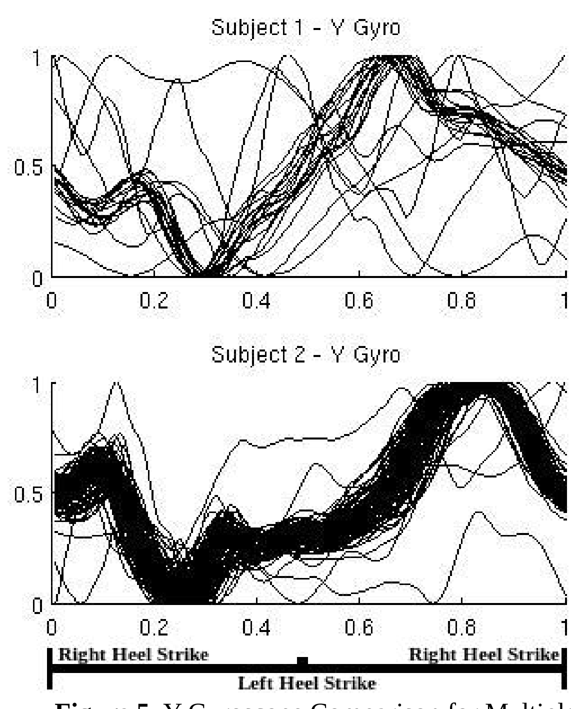

Figure 5. Y Gyroscope Comparison for Multiple Normalized Periods

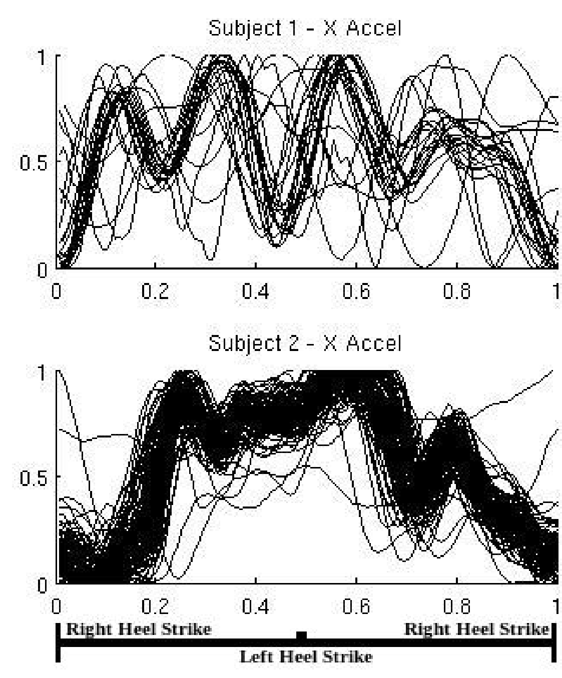

Figure 6. X Acceleration Comparison for Multiple Normalized Periods

The same approach of re-sampling was taken with the x acceleration, but in testing, it provided no advantage. Furthermore, when x acceleration values were coupled with only the x or y gyroscope the accuracy was lower. Therefore, in our feature vector, we exclusively focused on the x and y gyroscope values. It is still unclear why the x acceleration provides no further advantage when used in conjunction with the x and y gyroscope values.

More investigation proved that in addition to the two re-sampled signals, prediction accuracy improved when a few extra statistical values were added to the feature vector. These values are (normalized) time of global minimum and maximum for both the x and y gyroscope periods. These 16 values compose the feature vector used in this work. The subsequent experimentation and evaluation are conducted using this feature vector.

5. EXPERIMENTATION AND EVALUATION

To fully enable the Enhanced Service Area system described in Section 1, further development of the system is necessary and is discussed in Section 6. Nevertheless, a simple experiment and subsequent evaluations act as "proof of concept" that identification via gait is both possible and practical in terms of speed and memory requirements.

5.1 Data Acquisition

The experiment created a repository of multiple test subjects walking in varied ways. The experiment measured the gait for seven people in three distinct ways:

- Normal, straight-line walking
- Circuitous, multi-direction walking with stopping and starting
- Distorted speed, straight-line walking

Each type of walking was measured up to three times, producing a repository of 50 different extended walking samples by seven people. Each walking sample contains roughly 25-30 periods with the exception of one subject who had over 100 periods for a single walking sample. In testing, each sample was decomposed into its gait cycles. Each gait cycle of a particular individual, regardless of which walking sample it came from or what type of walking was measured, was given a label corresponding to that individual. Using this data set, we examined whether a period, described by its feature vector, could be accurately assigned to an individual whose gait had previously been measured and stored in the repository.

5.2 Results

The simple performance metric in this evaluation is precision. That is, performance is simply the percentage of returned labels that correctly specify the person who produced the gait cycle. Another common performance metric is recall. While precision is the percentage of returned labels that are correct, recall is the percentage of correct labels that are returned. Recall specifies the "covered set" of correct outputs. However, because this system will always assign a label, recall is equivalent to precision and thus, not presented. We evaluated the ability of the feature vector to adequately differentiate the gait cycles using K-Nearest Neighbor (K = 1, distance = sum of absolute differences), Naive Bayes and Quadratic Discriminant Analysis. We partitioned the data set in different ways.

Recall that each test subject produced normal, circuitous and distorted-speed walking samples. The first evaluation involved only the normal walking samples and shows 10-fold cross-validation performance. The second used 10-fold cross-validation on the circuitous walking samples only. The third evaluation used 10-fold cross-validation on the distorted-speed walking samples. The final evaluation used the entire repository of all 50 walking samples with 10-fold cross-validation. These results are presented in Figure 7.

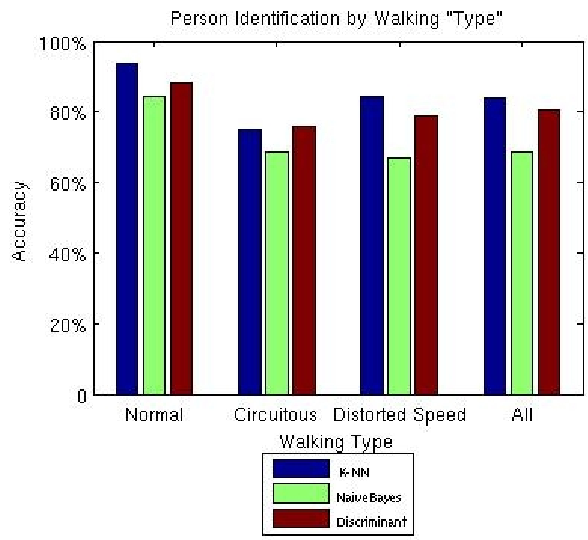

Figure 7. Accuracy Using Cross-Validation

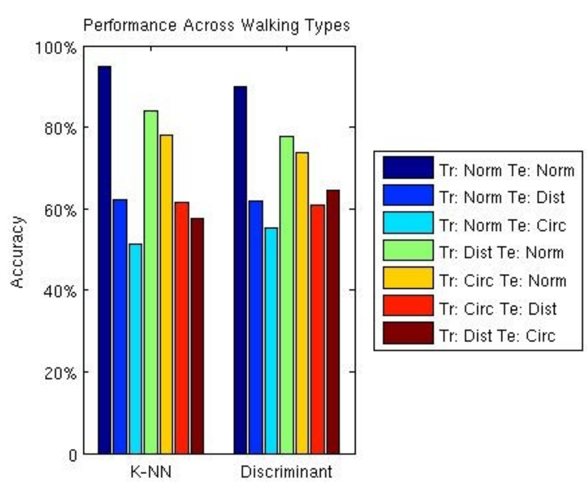

Figure 8. Accuracy Across Walking Types

Figure 8 presents performance for a different type of learning problem. In all but one of these evaluations, the classification method used one subset as training data, and a different type of walking as testing data. The first evaluation is different in that it trained on a total of ten normal walking samples from five people, and tested on a single normal walking sample for each of the five people. The evaluations were done for both K-Nearest Neighbor (K = 1, distance = sum of absolute differences) and Quadratic Discriminant Analysis. As Figure 7 indicates, Naive Bayes consistently performed the worst of the three methods in person prediction and is not shown in Figure 8.

An interesting result in Figure 8 is the first evaluation, which trained on two normal walking samples per person and tested on a single normal walking sample. The accuracy was roughly 95%. This suggests that in a cooperative scenario, such as the Enhanced Services Area, where subjects desire for the system to identify them, and thus, use their normal gait, the system is extremely practical. A disappointing result shown in Figure 8 is the generally poor performance of both classifiers in identifying a distorted or circuitous gait cycle when training on normal walking data. As mentioned previously in this work, it maybe be possible to eliminate certain gait cycles from a walking sample so that the only remaining gait cycles are true walking examples. It is believed that such an approach would increase the accuracy for training on normal gait cycles and testing on non-normal gait cycles. Future work is needed to address this shortcoming.

K-Nearest Neighbor generally performed the best throughout. It is our belief that extreme optimizations can improve the classification time significantly. However, even without optimizations, K-NN classified the testing set in less than 1 second in all cases. For a single gait cycle classification, as is the case in the Enhanced Service Area system, classification takes *at most* 100 ms. Although the results shown in this paper all use K = 1 for K-NN, other values for K were tested. K = 1 showed the best accuracy in every single case.

5.3 Comparison

The accuracy of roughly 95% is on par (slightly better) than the results found in some related work. Gafurov [4] achieved a low error rate of 7%. However, further comparison is difficult because that work [4] uses a repository that is an order of magnitude larger. Furthermore, that project also tests subjects carrying a backpack. Although the work in this paper did not test hands in pockets or burdened walking, the circuitous and distorted speed evaluations demonstrated significantly different walking patterns. Another noticeable difference in the two projects is that Gafurov [4] only utilizes six gait cycles from each walking sample, whereas the project in this work utilizes every gait cycle in the sample (after the 1.3g threshold has been surpassed). It is likely that choosing only the six most similar gait cycles per sample would increase performance using our method considerably. These comparisons should be addressed in future work, however, with the Enhanced Service Area as the target application, it was determined that all gait cycles should be used in order to simulate a real-time, constantly updated system. Lastly, it is important to point out, once again, that this work is believed to be the first to use wearable gyroscope sensor data to identify people. Most related work in the field of wearable sensors utilizes accelerometer sensor data.

6. DISCUSSION

The work in this project is still in its early stages and needs further analysis in several areas. Although the Enhanced Service Area was the motivating target application for this paper, there are several other applications to which this approach may be applicable. Future work on this project should address as many issues as possible, as well as further develop the system to enable these new applications.

6.1 Limitations and Issues

This approach in its current form is obviously most limited by the fact that it requires the individual to carry the remote in their pocket. This requirement relegates the approach to cooperative environments, where the user desires that he/she be identified by the system. Nevertheless, it is believed that cooperative environments will make up a substantial proportion of future smart environments.

Another issue with this work is that it does not examine thoroughly enough how best to determine which gait cycles to use or discard. The current system uses every gait cycle found, regardless of whether it is the product of walking. If there is a way to ignore noisy gait cycles, the accuracy could be improved significantly. Also, it is important to note that in most of the targeted systems for this approach it is probably not necessary for every gait cycle prediction to be correct, but rather that a majority of the recent predictions be correct.

This work could also be improved by using a larger database of walking samples and a larger variety of classification methods. Although the feature vector and the three methods used were adjusted to the full extent possible, simply using other classifiers may prove to be valuable. Another issue for investigation is why the x acceleration signal did not improve the accuracy of the classification methods. The fact that it was not as valuable for prediction as the x or y gyroscope could be simply that it *is* just not as valuable, or it could be a flaw in the underlying model. Lastly, it may be beneficial to approach the problem one level above the gait cycles. If the sequence of gait cycles was used, rather than single gait cycles, it is possible that a Markov approach or even Naive Bayes would perform well through the exploitation of the sequence from one gait cycle to the next. This concept, however, seems to undermine the fundamental principle of human gait: that it is periodic.

6.2 Future Work and Applications

Further development is needed in two key aspects of this work. First, it should be investigated how the accuracy is affected when a person is bearing a load, holding the device in their pocket, or carrying the device in a different place than their pocket. Second, the system should be extended so that the Enhanced Service Area scenario is complete. This extension would require the ability to take a real-time, incoming signal, parse its gait cycles on the fly, and return a prediction for the identity of the individual. Another enhancement would be if the system could identify a new person that it has not seen before. This would enable the system to learn online in a real world deployment.

The Enhanced Service Area application is a practical, imaginable and fairly wide-reaching scenario to motivate this work, but other potential applications exist. These include simple authentication scenarios where a user enables their gait signal to be transmitted to the environment as they approach a locked door. The system could analyze the gait to identify the person and unlock the door accordingly. Another example application is the futuristic concept of User Spaces, where a user's device enables a personal network on top of existing wireless and wired networks. These User Spaces would enable a new level of connectivity and sharing [6].

7. CONCLUSION

This paper proposes a biometric method for identifying people based on their gait. It uses a device that combines an accelerometer with a gyroscope to record the force of a person's walk in 6 directions. Using a direct form transpose filter, gait cycles are extracted from the signals and analyzed for their characteristic features. Simple classification methods were employed to classify a gait cycle based on its similarity to other gait cycles. Three different types of walking were recorded during experimentation, with the focus of this work on successfully identifying the “normal” walking gait cycles. With 95% accuracy, this approach is able to identify to which person a gait cycle belongs. An example scenario of the Enhanced Service Area was proposed as a motivating application, but it is the belief of the author that in the near future there will be an explosion of applications able to exploit such an identification approach.

8. ACKNOWLEDGMENTS

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