Human Identification by Gait Analysis

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ABSTRACT

Human movement monitoring using wireless sensors has become an important area of research today. The use of wireless sensors in human identification is a relatively new idea with interesting applications in portable device security and user recognition. In this paper, we describe a real-time wireless sensor system based on inexpensive inertial sensors that uses gait analysis to uniquely identify subjects.

Categories and Subject Descriptors

I.5.4 **[Pattern Recognition]:** Applications – *Waveform Analysis*
J.3 **[Life and Medical Sciences]:** *Health*
C.3 **[Special-Purpose Application-Based Systems]:** *Real-time and Embedded Systems*

General Terms

Design, Experimentation, Security, Human Factors.

Keywords

Gait Analysis, Segmentation, Biometrics, Body Sensor Networks.

1. INTRODUCTION

Wearable inertial sensors have several applications such as locomotion monitoring and healthcare monitoring, as described in [1] and [2]. Specifically, these sensors can be used in rehabilitation, sports medicine, geriatric care, and gait analysis. In these applications, the goal is typically to identify the movement performed by a subject regardless of the identity of the subject. In contrast, the application of human identification requires identifying a subject based on performance of a known movement.

Biometrics such as fingerprint recognition and iris recognition have been employed widely to uniquely identify people. Gait identification has been proposed as another such biometric and has been studied for more than a decade. It involves analyzing the walking pattern of a person and identifying features that can be used to distinguish one person from another. Gait-based identification can be used separately or in conjunction with other biometrics to establish the identity of a person. It can also be used to secure portable devices such as mobile phones, wearable computers, intelligent clothing and other smart devices [3]. Other methods proposed for portable device security, such as signature- and fingerprint-based techniques, are explicit and require user attention. In contrast, gait-based human identification is implicit and unobtrusive.

We will demonstrate a wearable sensor system that can be used for human identification based on gait analysis. Section 2 discusses related work, section 3 describes our system architecture, section 4 describes the gait identification application, and section 5 describes the demo setup.

2. RELATED WORK

Most existing gait identification techniques are based on machine vision [4,7] or floor sensor technology [5]. In the machine vision approach, gait is captured using a video-camera from distance. Video and image processing techniques are employed to extract gait features for identification purposes. In a floor sensor-based approach, a set of sensors or force plates are installed on the floor. Gait related features are measured when a person walks on them.

The use of wearable sensors for gait identification is a recent area of research. The authors of [3] have used wearable sensors for gait identification; however their technique differs from ours as they have used different methods for segmentation and recognition. Specifically, their segmentation algorithm finds local minima and maxima and their recognition technique is based on signal correlation and uses Fourier analysis. We chose to avoid the frequency domain to decrease algorithmic complexity and are using more formal pattern recognition techniques for recognition. Another difference is our segmentation approach, which starts by finding the walking period and then finds just one minimum per period. This tends to avoid problems with noise or unusual gait creating spurious local minima.

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3. SYSTEM ARCHITECTURE

Our system consists of two wireless sensor nodes: one sensor unit with a custom-designed sensor board and a base station. The sensor unit has a tri-axial accelerometer and a bi-axial gyroscope, as shown in Figure 1. The sensor node samples sensor readings at 20 Hz and transmits the data wirelessly to the base station. The base station is connected to a laptop via USB. It forwards the sensor readings it receives from the node to the laptop. Our sensor node is the Tmote Sky, is commercially available from motiv®, is powered by two AA batteries, and uses the TinyOS operating system [6].

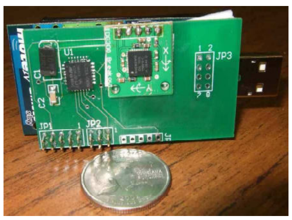

Figure 1: Sensor node with inertial sensors

4. GAIT IDENTIFICATION

To identify humans based on gait we follow the signal processing flow shown in Figure 2. First we receive five signals from the sensor unit: x acceleration, y acceleration, z acceleration, leg pitch and leg roll. The orientations of these signals with respect to the leg are shown in Figure 3. The signals are filtered and segmented automatically into gait cycles. Features extracted from these segments are given to a classifier to perform identification. Sections 4.1 and 4.2 detail our segmentation and classification techniques, respectively.

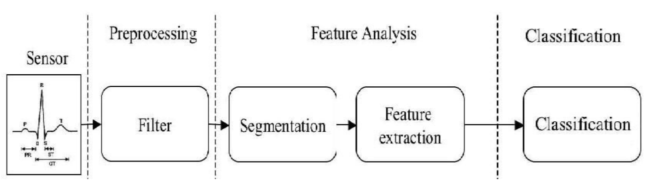

Figure 2: Signal processing flow

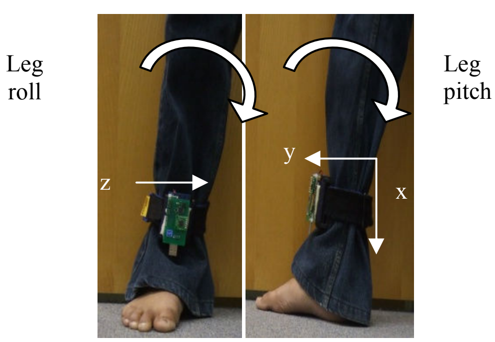

Figure 3: Leg Roll and Leg Pitch

4.1. Segmentation

The gait signals obtained from an individual are composed of periodic segments called gait cycles. These cycles correspond physically to two consecutive steps of the individual. A gait cycle begins when one foot touches the ground and ends when that same foot touches the ground again. The end of one gait cycle is the beginning of the next. To split the signal into gait cycles, we first need to determine the period of the gait cycle. Then, we can find the start of a gait cycle within the approximate period of the signal.

To find the period of the gait cycle, we find the offset T such that the signal shifted by multiples of T is the most similar to the original signal, where T cannot be zero. To find T, we first calculate the following function:

$$D(\tau) = \int [f^2(t) - f^2(t+\tau)]^2 \, dt$$

This is the sum of the square of the difference between the power of the signal and power of the signal shifted by τ, where $f(t)$ is the signal. This function has been used as a measurement of the consistency of locomotion, where consistency refers to the similarity of one gait cycle to other gait cycles and includes both consistency in time and consistency in space [1]. For approximately periodic movements, $D(\tau)$ is approximately periodic and has the same period as the original signal. The intervals between minimums of $D(\tau)$ indicate the expected period of motion (T), as shown in Figure 4.

We expect to find the start/end of a gait cycle every T seconds. The minimums in the leg pitch signal indicate the start/end of a gait cycle. We find the first minimum in this signal and use windows of size T to find the next minimum. The window is shifted by $T/2$ from the last point found, and the absolute minimum within that window is considered the start of the next gait cycle. An example of the segmented signal is shown in Figure 5.

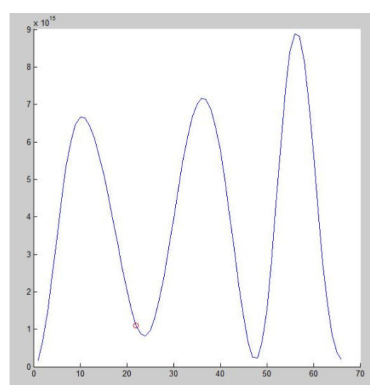

Figure 4: $D(\tau)$ when a person is walking- time between troughs represents the period of a step

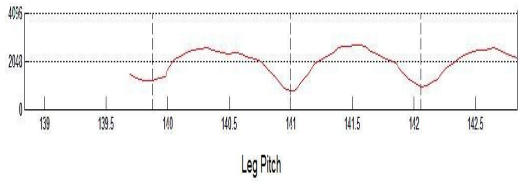

Figure 5: Leg Pitch signal segmented at the minima

4.2. Recognition

After gathering data, 100 features were extracted from each segment, 20 from each of the five sensor streams. The features calculated for each sensor stream were mean, median, standard deviation, RMS value, amplitude, maximum value, minimum value, peak to peak value, variance, start to end amplitude and 10 morphological features. Linear Discriminant Analysis (LDA) was used to select the best features prior to classification. The 30 features with the highest weighting in the LDA projection matrix were given to the classifier, increasing the classification accuracy of the system by about 20%. The maximum value, minimum value, and RMS value were found to be the best features for our analysis. The k-Nearest Neighbor (k-NN) classifier with k=1 was used for gait identification. The k-NN classifier was chosen for its simplicity, scalability and small memory requirement. The classification accuracy was 84% for 4 subjects (2 male and 2 female, with ages ranging from 23 to 32). Each person submitted one test trial and one training trial with eighteen steps in each trial. Each trial was segmented into gait cycles, and each step was separately identified. Majority voting was used to determine which subject generated the test trial. This gave us an identification accuracy of 100%. We expect this accuracy to decrease if we use a larger training corpus.

5. DEMO SETUP

For the demo, a sensor unit will be placed on the right leg of the volunteers, at the ankle, as shown in Figure 3. The sensor unit will be attached to the volunteers with a Velcro sports band. The sensor readings and the graph of $D(\tau)$ are observed when the volunteer is walking. It takes some time (about 3 steps) for the system to start segmenting the signal into gait cycles. When we observe the signals being segmented into gait cycles, we begin to save data. The volunteers will walk at a normal pace without stopping or turning until we have saved 20 steps. This is the training data provided to the classifier. One (or more) of these volunteers will walk 20 steps again in the manner described above. This will be the test data to the classifier. Classification will be performed to identify the testing volunteer(s) from the training volunteers.

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