onds, and then processes the sample (i.e., feature extraction and classification) to obtain the classification result. The value of T directly impacts the total authentication latency; larger T values lead to longer authentication latencies. From our preliminary investigation, we further take note that the processing delay increases more than linearly with sample duration – e.g., processing a 2-second sample takes 1.29 seconds, while processing a 10-second sample takes 20.48 seconds (according to Figure 7). As a result, we would like to have lowest possible T values. On the other hand, however, having a too small T value may lead to inferior authentication accuracies. What further complicates the problem is that we find that it is impossible to find the uniformly optimal T value for different users. Thus optimizing this important parameter across different users becomes a serious challenge.

In this project, we propose to address this challenge by adopting the well-known pipeling technique, which is motivated by the characteristics of *Headbanger*. Suppose the original signal duration is T, and we have $T = nt$ with n being an integer and $t < 2$ seconds. Let us assume that the processing delay is less than t when the sample duration t is less than 2 seconds. Then we can explore the following pipelining method. In the first t-second window, the system collects the *ACC* sample for t seconds. In any subsequent t-second window, the system continues to collect the *ACC* sample for t seconds, and at the same time, processes the portion of the sample collected in the previous window. We refer to this method as *pipelined authentication*.

The proposed pipelined authentication can reduce the overall authentication latency in several ways. First, we overlap data collection and data processing to reduce the overall delay. Second, since processing shorter samples incurs less (than linear) latencies, by breaking a sample into smaller chunks can reduce the total latency. For example, using the numbers presented in Figure 7, we find that processing one 10-second sample takes much longer time than processing one 6-second, one 2-second, and two 1-second samples. Third, now we can conduct what we call "early classification" – maybe using a portion of the sample can already reveal the classification result – and then we don't need to collect/process the entire sample. That is, we can dynamically determine the shortest sample duration we need. Combing these factors, we can achieve much reduced authentication latency (i.e., shorter data collection and shorter processing delays). Figure 8 illustrates the benefit of the proposed pipelined authentication scheme.

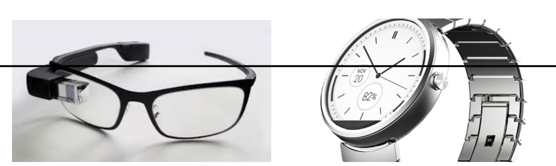
Authentication with Fewer Samples: Another optimization we will explore is authenticating users with fewer samples. We can attempt to reduce the number of samples in several ways. First, we can minimize the number of samples for the legitimate user in the training set. It is thus a tricky question to determine how many and which samples should be used. In this project, we will explore only using the "representative" samples – i.e., those that are the most similar to the rest of the user's samples. In this way, the computation/energy consumption in the authentication session can be greatly reduced.

Another optimization technique we can adopt is to dynamically adjust the sampling rate in the test phase. A lower sampling rate leads to fewer data points in a sample, thus shorter collection and processing latencies. In this project, we will explore dynamically adjusting the sampling rate based upon the temperature of the device. Namely, if we notice the device is becoming heated, then we should reduce the sampling rate. In the project, we will carefully quantify the interaction between the device temperate and the sampling rate.

5 Evaluation Plan

5.1 Developing *Headbanger* App on Google Glass and Moto 360

In this proposal, we propose a body-movement pattern based authentication system, *Headbanger*, for wearable de-



(a) (b)

Figure 8: We will implement *Headbanger* on (a)

vices. In addition to developing and evaluating the proposed algorithms, we will also conduct in-depth evaluation of the *Headbanger* system design. Even though there are many types of body movements that we can exploit for authentication purposes, in this project we will focus on the movements that can be easily captured by Google Glass (representing smart glasses) and those by Moto 360 (representing smart watches). Specifically, we will study the following movement patterns:

- *Movement patterns for smart glasses:* As far as smart glasses are concerned, we will explore head movement patterns (with music), eye blinking/winking patterns (with music), and pulses measured at the temple.
- *Movement patterns for smart watches:* As far as smart watches are concerned, we will explore arm movement patterns (with music), wrist movement patterns (with music), finger movements (with music), and pulses measured at the wrist.

We will choose easy-to-follow and fast-tempo music tracks (10 seconds long) as external stimuli. The readers can download such an audio track at our web site: *http://www.winlab.rutgers.edu/ sugangli/somebody.midi*.

5.2 Data Collection

The key to the success of this project is to collect data from a large and diverse set of participants, in different environments and contexts. In this three-year project, we plan to collect data from 30 subjects. We will make effort to recruit participants such that we have a balanced mix of gender, age, height, and handedness. We plan to pay each subject $15 for their particpation.

Figure 10: Our team member was collecting data with one of the participants in the preliminary study.

In the data collection session, we will inform the participants of the potential risks involved in wearing Google Glass and collecting head-movement or eye blinking/winking/pulse data (e.g., feeling dizzy after head-movement for a period of time, not being able to see clearly if near-sighted, etc.), as well as the potential risks in wearing Moto 360 and collecting hand-movements/pulse data (e.g., wrist pain). If they agree to participate, we will ask each subject to report their age and gender. We will help the subjects to wear the Google Glass and make head movements and eye blinking/winking while listening to the music track of their choice. We will also help the subjects to wear the Moto 360 and make wrist/hand movements while listening to the music track of their choice. Meanwhile, we will record the raw accelerometer data, raw gyroscope data, and the infra-red sensor data from the Google Glass. Each recording session will be 10 seconds long, and we (the graduate students) will sit through each session with the subject to help him/her use the system properly, as shown in Figure 10. After every 5 recording sessions, we will ask the subject to take a break to relax their muscle and regain energy. We will also split each subject's data collection session on different days, to include natural movement variability in the data sets.

5.3 Long Term App Deployment and Evaluation

After evaluating and revising the app design using realistic user data, we will install the *Headbanger* app on five Google Glasses and five Moto 360 watches. We will ask ten participants to use these devices on a daily basis for three months. During the evaluation period, each participant is the legitimate user of the device, and they will invite friends and family members to try to log in to the device from time to time. The authentication records will be logged and synced to the cloud, which we will monitor remotely. After the