by evaluating these features, and propose to look at the following features in depth: (1) mean, standard deviation, median, 25%, and 75% of frequency (in the frequency domain), (2) mean low and mean rectified high pass filtered signals (in the frequency space), (3) centroid frequency (in the frequency domain), (4) frequency dispersion (in the frequency domain), (5) power spectrum of entropy in acceleration/rotation and average energy in acceleration/rotation (in the frequency domain), (6) magnitude of first five components of FFT analysis (in the frequency domain), (6) jerk index that indicates the smoothness of the signal (in the time domain), (7) mean crossing (in the time domain), (8) maximum difference acceleration (in the time domain), (9) correlations between axes (in the time domain). We will conduct an in-depth comparison of these features, and select those that deliver the best performance; meanwhile, we will also design new features that are suitable for our study.

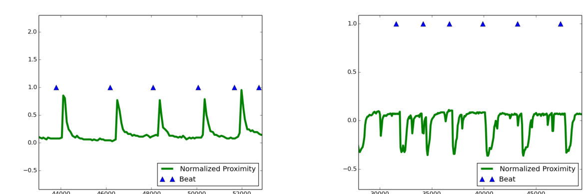
**Boosting Information Entropy:** It is important to encode as much information as possible into the observed sensor signals to achieve higher information entropy. One way of achieving this goal is to have the user move her body naturally following an external music stimulus – we hypothesize that different people translate music stimuli to motor movements in different ways [9, 16, 22]. For example, some people are able to follow beats much closer than others, some can follow beats more regularly than others, etc. By using the music stimuli, in addition to the afore-mentioned baseline $ACC/GYRO$ features, we can also consider a group of new features concerned with the temporal relationship between music beats and subsequent body movements – such as mean and standard deviation of the intervals between a music beat and the subsequent body movement, the top interval values, etc. In this way, the sensor data contains more information than just the movement pattern.

In order to further boost the information entropy, we can also switch the music track during a data collection session. In this way, the sensor data does not only contain the user's motor response to the music beats in a steady state, but it also encodes information about how fast the user adapts to the change of music rhythm, which provides more discrimination power.

#### 3.2.2 User Authentication Through Combined Movements and Sensors

Smart wearable devices typically contain an array of motion sensors such as accelerometer, gyroscope, and inertial measurement unit (IMU). It is only a matter of time that motion sensor chips will be integrated into wearable devices. This opens up opportunities for multi-modal motion sensing. For example, accelerometer data can be combined with gyroscope measurements to provide multi-dimensional movement features that can improve the quality of the inferred signatures. Head movements can also be combined with other body movements to generate valuable, reliable signatures for authentication. In this project, we plan to explore these opportunities.

**Combining Multiple Movement Signatures:** In our preliminary study, we only looked at monitoring head movements for authenticating Google Glass. In reality, there are other types of movements that can be captured by Google Glass for authentication purposes. For example, through a simple test experiment using the Google Glass infra-red light sensor we observed that the blinking and winking patterns of users in response to the music can be combined with head-movements for better results. For example, Figure 4 shows two users' blinking pattern (captured by the infra-red light sensor, or the proximity sensor) with respect the music tones are vastly different. Recent studies have also shown that heart beat or pulse can be read by Google Glass [38]. In this project, we will look at whether these signals can be combined to obtain better classification results.




(a) (b)

Figure 4: A person's blinking patterns (measured by the infrared proximity sensor on the Google Glass) with respect to music beats are also differentiable.

The main challenge in combining multiple movements stems from the fact that it is hard to separate their impacts on motion sensor readings (e.g, the fact that a user winks may change the way she moves her head). As a result, if not properly handled, combining movements may actually worsen the authentication results. In this project, we will carefully investigate what new features we will exploit if multiple movement patterns are combined.

**Combining Accelerometer and Gyroscope:** Quite a few previous studies have looked at combining accelerometer and gyroscope readings to detect motion contexts such as walking, standing or fall [61, 50, 55, 107, 89, 75]. In our preliminary study, however, we find that gyroscope data from Goolge Glass fared very poorly in discriminating users' head movements. The reason is that gyroscope often drifts over time. Low pass filtering can help cancel such drifts, but it also erases much useful information in the low frequency range, thus rendering it less useful. On the other hand, complimentary filters (discuss in [27]) that combine accelerometer and gyroscope readings could provide attitude estimation. It performs low-pass filtering on a low-frequency attitude estimation that is obtained from accelerometer, and high-pass filtering on a high-frequency attitude estimation that is obtained by the integration of gyroscope data. Though better than low-pass filtering alone, this may also lead to information loss in the low frequency range, hence poorer classification results. In this project, we will try to develop a signal processing method that can better preserve information in the low-frequency range.

**Authenticating Multiple Devices:** When a person has multiple wearable devices, we don't need to authenticate the same user to different devices one by one (assuming these devices are not put on at the exactly the same time). Instead, after the user is authenticated on the first device, the first can help the user authenticate on the second device by having the user make simple and short body movements that can be measured by both devices (e.g., shaking two devices using one hand each) [62, 70].

### 3.2.3 Robust Authentication in Mobile Settings

Our preliminary results show that head movements are rather distinctive and repeatable in very controlled settings – all the data were collected when the participant was in a stationary setting, i.e., sitting on a chair. However, in reality, the behavior of body movement signatures over chaotic settings will be a key factor to decide on the effectiveness of this approach. In this project, we strive to solve the challenge for the most common mobile setting: when the user is walking.

**Authenticating Walking Users:** For a walking user, we can't rely on the original training data that is collected when the user was sitting or standing still any more; performing body movements while walking will definitely lead to different movement signatures.

When considering walking, we can collect sensor readings in three different scenarios (we only focus on $ACC$ data in this part for the sake of simplicity): $ACC_{M+W}$, denoting the sensor readings when the user is performing body movements while walking; $ACC_M$, denoting the sensor readings when the user is performing body movements while sitting or standing still; and $ACC_W$, denoting the sensor readings when the user is walking, without any special body movements. To address the challenge of authenticating walking users (whose test data is $ACC^{tst}_{M+W}$), a naive method is to use an external accelerometer (such as the one on the smartphone) to record the motion caused by walking ($ACC^{tst}_W$). We can then extract the motion caused by special music-stimulated body movements as

$$ACC^{tst}_M = ACC^{tst}_{M+W} - ACC^{tst}_W.$$

Finally we can compare $ACC^{tst}_W$ with the reference data $ACC^{ref}_W$ to classify the user. Though simple and effective, this method does require another device, which is less convenient, as we have argued before. As a result, we will *not* adopt this method in the project.

If we only use the accelerometer on the device, authenticating a walking user becomes much harder, mainly because a person's walking pattern is much less repeatable – factors such as trajectory, speed, terrain will have a bearing on the walking pattern – and the interaction between walking and music-stimulated body movements are very complex and hard to predict. Due to the complexity of this problem, we will explore a learning-based authentication approach. In the

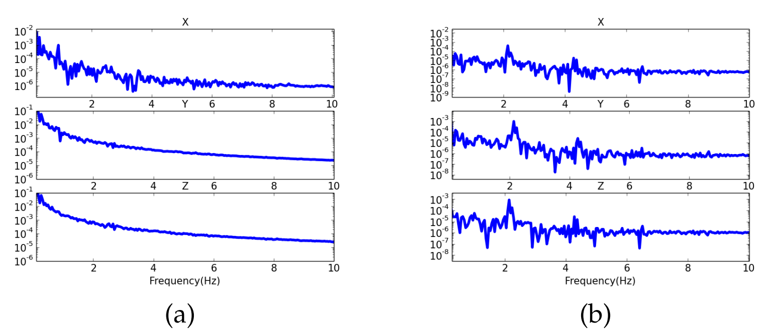



Figure 5: Walking (a) usually has more energy than music-stimulated partial body movement such as nodding (b).