The Smart Floor: A Mechanism for Natural User Identification and Tracking

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ABSTRACT

We have created a system for identifying people based on their footstep force profiles and have tested its accuracy against a large pool of footstep data. This floor system may be used to identify users transparently in their everyday living and working environments. We have created user footstep models based on footstep profile features and have been able to achieve a recognition rate of 93%. We have also shown that the effect of footwear is negligible on recognition accuracy.

Keywords

Interaction technology, ubiquitous computing, user identification, biometrics, novel input.

INTRODUCTION

In the Smart Floor project, we have created and validated a system for biometric user identification based on footstep profiles. We have outfitted a floor tile with force measuring sensors and are using the data gathered as users walk over the tile to identify them. We rely on the uniqueness of footstep profiles within a small group of people to provide recognition accuracy similar to other biometric technologies. Specifically, we have been able to achieve a 93% overall user recognition rate with our system, and have been able to show that footwear is not a significant factor in identifying users. Furthermore, we have created a system that can transparently identify users and now allows us to prototype useful services for users.

While there are other biometric user identification techniques that work well, such as face recognition from video or voice recognition from audio, the Smart Floor provides capabilities that these other technologies do not. Face recognition generally requires that the user not be occluded and that shadows and lighting problems are minimized; many systems require a good close-up frontal picture of the face. Voice recognition typically has problems in noisy environments. Our system is not plagued by any of these problems. Like these other transparent biometric technologies, however, users do not need to carry a badge or other device that explicitly identifies them to the system. However, we do not claim that our Smart Floor is a replacement for these other technologies; it is part of a further exploration of the space of transparent biometric identification. Specifically, the floor affords different interactions than these other technologies. With thoughtful design and placement of our floor tiles in a workspace or living space, we can naturally and transparently capture a user's footfalls without requiring the user to alter his or her behavior.

Our goals for the Smart Floor system included creating an accurate system for recognizing a user's identity from their footsteps, and showing that for a small group of users (up to about 15), different users footstep profiles are dissimilar enough for our system to achieve reasonable accuracy. In this paper, we will describe the progress we have made towards these goals.

EXPERIMENTAL SETUP

In the biomechanics literature, the reaction that a measuring device produces in response to the weight and inertia of a body in contact with that device is called *ground reaction force* (GRF). In our case, we are measuring the GRF of the user's foot as he or she walks over our measuring tile. The hardware we have used to gather GRF profiles consists of three components: load cells, a steel plate, and data acquisition hardware; this setup is partially shown in Figure 1.

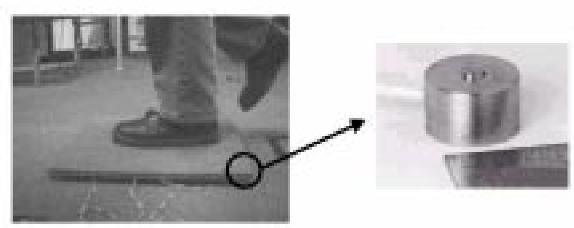

Figure 1. *Smart Floor plate (left) and load cell (right).*

In modeling each user's footsteps, we have chosen ten footstep profile features to use as markers for each GRF profile, as shown in Figure 2. Our features include: the mean value of the profile; the standard deviation of the profile; the length of the profile (the number of samples); the total area under the profile curve; the coordinate of the maximum point in the first half of the profile (x_{max1} and y_{max1}); the coordinate of the maximum point in the last half of the profile (x_{min} and y_{min}); and the coordinate of the

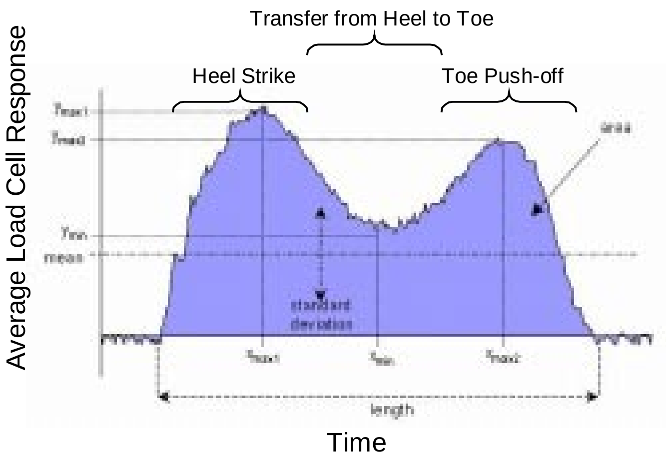

Figure 2. *Footstep profile features.*

minimum point between the two maximum points (x_{max2} and y_{max2}).

We place training footsteps into a ten-dimensional feature space and use a nearest-neighbor search to match new unidentified footsteps with the identity of the closest cluster from the training set. Each feature listed above, once normalized, is one dimension in this ten dimensional space. We refer each combination of user, foot, and shoe type as a condition (e.g., "Joe's left foot while he was wearing tennis shoes"). One condition of a given user's training footsteps constitutes one cluster of data in the training set. Given a new and unidentified footstep, we calculate the Euclidean distance from the unidentified footstep to every footstep in every cluster. The identity of the cluster with the lowest average distance is chosen as the identity of the unknown footstep.

RESULTS

We gathered GRF profiles from 15 subjects, 12 male and 3 female. For each subject, we gathered separate data for left and right feet. We also attempted to gather data for as many shoe types as possible. We also gathered 20 footsteps per condition, half of which we would use for training and half for testing. In total, we gathered 1680 footstep profiles.

In calculating identity, we counted as correct any result that gave the correct user, regardless of whether the correct shoe or foot was given. Using the footstep clustering method described above, we were able to achieve 93% correct identification.

Furthermore, the test data gathered reveals that in 88% of the cases, a user's footfalls are more similar to other footfalls for that same user than to footfalls for another user. We conclude from these results that *footwear does not greatly affect the ability of our approach to identify the user by his footsteps*.

FUTURE WORK

We are currently working to determine which of our ten features is most important in recognition. By weighting all ten features equally, we may be inadvertently increasing the distance between related footsteps and lowering our accuracy. By properly weighting the features, we may be able to bring related footsteps closer together in feature space and raise our accuracy [2]. Our preliminary analysis indicates that area under the curve and standard deviation from the mean are the two most important features.

RELATED WORK

Addlesee, et al. [1] have designed a system similar to ours, except they used hidden Markov models (HMMs) to perform user recognition. They achieved recognition accuracies similar to ours (91% correct). Our approach, however, makes explicit the features used in the recognition process. This has allowed us to investigate in detail the similarity of footsteps across footwear, and to determine which footstep characteristics are most important in identification. Furthermore, the computational requirements of our method are much lower than an HMM-based approach.

CONCLUSIONS

We are planning to deploy the Smart Floor in the Georgia Tech Aware Home, a technologically advanced house that will serve as a living laboratory for a number of experimental technologies. We will install ten Smart Floor tiles in strategic locations, including house entrances, hallway entrances, kitchens, and bedroom entrances. In addition to giving identity and implicit location within the house, the tiles also indicate the direction in which the user is traveling (simple temporal comparison of the load cell peaks yields this).

We are very interested to observe how everyday users will interact with and react to our Smart Floor system. For example, we are concerned that the users have control over the functioning of the system. To this end, we may be able to use the data gathered by the system itself to control the system. For example, very high amplitude input, such as a "stomp" footstep, could instruct the system to turn off user recognition until the next time it sees another stomp. Other types of floor "gestures" may be associated with other system actions.

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