

# Gesture-Based Peer-to-Peer Pairing Authentication for Asymmetric Internet of Things Devices

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## 1. PROJECT PROPOSAL

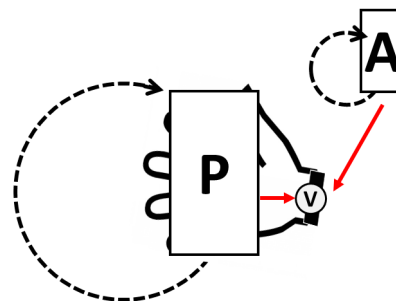
In an Internet of Things (IoT) environment, mobile devices may need to pair or authenticate themselves to other devices. However, unlike the traditional internet, an IoT environment does not typically have a centralized certificate authority, making it difficult for one device to determine if another device is authentic. Furthermore, these IoT devices are often resource-constrained, meaning traditional cryptographic defenses that support confidentiality, integrity, and authenticity difficult to implement [5, 16].

One potential solution to this problem is to use biometrics—especially motion and gestures—in order to validate the identity of the device. Prior work has shown that impostors has a low probability of imitating a gesture calibrated to another person successfully [3]. Furthermore, motion recognition is suitable for IoT systems which feature small sensors and low powered devices because motion recognition can achieve high accuracy with just an accelerometer [14].

Some prior work have looked at motion sensor data fusion across different devices to detect pairing, for example detecting device collision when tiling two tablets together [6]. Existing work in gesture recognition and event detection focuses on gestures on the same device or similar devices (e.g. two tablets, gestures on a Wiimote [10]). However, pairing in an IoT environment is usually needed for two asymmetric devices with different types of hardware sensors (e.g. a smartwatch with a smartphone).

In this project, we propose to analyze the use of gestures as a biometric for peer-to-peer authentication in an IoT scenario, where sensor devices are asymmetric. Our project will analyze the following three key defense models for authentication.

- *Model 1:* This system model contains three entities: a legitimate prover, a verifier, and an attacker. The legitimate prover is non-malicious and wants to pair with the verifier. Both the legitimate prover and the verifier are owned by the same person (e.g. a smart-



**Figure 1: System model for defense model 1. The verifier (V) and the prover (P) are synchronized in motion. The attacker (A) must try to mimic the motion of the verifier in order to trick the system.**

phone and a smartwatch). However, the attacker is a malicious prover and wants to also pair with the verifier. To distinguish between the attacker and legitimate prover, the verifier uses gesture recognition to distinguish between the two parties.

Since the legitimate prover and verifier are owned by the same person, the user performs any generic gesture while holding both devices as shown in Figure 1. Accelerometer data is used to read the gesture, and a matching gesture authenticates the prover.

In contrast, the attacker must mimic the gesture of the verifier in order to trick the verifier. Our hypothesis is that we can keep false negatives (rejecting legitimate provers) and false positives (accepting attackers) to less than 10%. This is modest compared to existing works due to the hardware asymmetry.

- *Model 2:* This system model contains the same three entities as in Model 1. In this model, the verifier has previously calibrated a single secret gesture with the user that is needed to pair with the device as shown in Figure 2. Devices that want to pair with the verifier must produce accelerometer data that matches this gesture with no prior knowledge about the gesture. Since this gesture is a predefined secret, only the prover needs to collect accelerometer data during the proof of authenticity.

An attacker may try to trick this model in the following two ways. First, if no information about the secret gesture has been leaked to the attacker, it will attempt

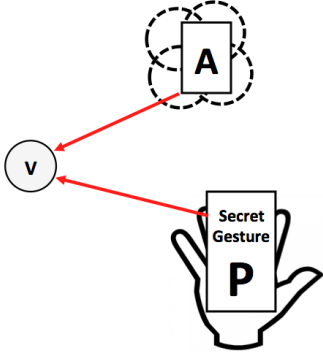


Figure 2: System model for defense model 2. The verifier (V) and the prover (P) are not synchronized in motion, and the verifier has previously established a secret gesture for pairing. The attacker (A) can brute force a gesture if it has no knowledge of the secret gesture, or it may imitate a gesture that it sees that a legitimate prover used.

a brute force attack and attempt several common gesture shapes, such as a circle, line, or even just shaking the device. Second, an attacker may learn information about which gesture is the secret gesture by watching a legitimate prover validate themselves to the verifier. These visual clues then reveal what the actual gesture is, and the attacker scenario reduces to the same as in Model 1.

For the second attack, we hypothesize that we will again achieve less than 10% false negatives for legitimate provers. However, we hypothesize 0% false positives for attackers if the secret gesture is not within the library of brute force attempts (i.e. the gesture recognition algorithm works).

- *Model 3:* The final model once again contains the same three entities as the prior models. Although similar to Model 2, this model establishes a pre-defined library of gestures at the verifier previously calibrated by the user. During the pairing process, the verifier will challenge the prover to a subset of the gesture library. As shown in Figure 3, the verifier sends visual prompts about what the gestures should be during the challenge process (i.e. the library of gestures is public). However, to trick the system, an attacker must produce the gesture in the same way as the intended user.

We hypothesize that there is an inverse correlation between number of gesture challenges and number of false positives (i.e. more challenges reduces the success of an attacker). However, we also hypothesize there is a direct correlation between number of gesture challenges and number of false negatives (i.e. there are more opportunities for the user to fail). We seek to find a threshold that minimizes the number of false positives and false negatives in this model.

## 1.1 Existing Tooling & Research Platform

We aim to use uWave [9, 10], an algorithm developed at Rice, for gesture recognition during our security analysis.

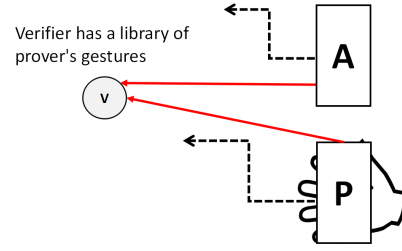


Figure 3: System model for defense model 3. The verifier (V) and the prover (P) are not synchronized in motion, and the verifier challenges the prover with a series of gestures in its pre-calibrated library. The attacker (A) receives the same prompts, but must mimic what the prover would do for each gesture.

This algorithm is simple and efficient that even simple 16-bit microcontroller can do the computation.

To test asymmetric pairing between different devices, we plan to use an android smartphone, an iPhone, and also another device with an accelerometer (the details of this IoT style device is to be determined after discussion with people from uWave team). Ideally, we will test pairing across each of these 3 devices with a smartphone app.

## 1.2 Project Milestones

- ~~March 16:~~ Setup programming platform for our mobile devices.
- ~~March 23:~~ Extract raw accelerometer data from each mobile device.
- ~~March 30:~~ Progress report due. Integrate raw data with the existing gesture recognition algorithm. Early comparisons of synchronized vs non-synchronized gestures.
- *April 6:* Gino extracts Android accelerometer data to computer. Henry sends iPhone accelerometer data to computer. Joe will integrate Wiimote with uWave.
- *April 13:* Demonstrable apps. Rigorous test data collection complete.
- *April 22:* Project completed.
- *Final Exam Period:* Final project presentation

## 1.3 Division of Labor

- *Joe:* Will contact the uWave researchers. Work to integrate a third mobile device with an accelerometer into the system (potentially the Wiimote).
- *Zulong:* Lead for Android software development.
- *Heng-Yi:* Lead for iOS software development.

## 2. RELATED WORK

Our related work is divided into three key categories: (1) gesture recognition algorithms and implementations on a single accelerometer device, (2) device pairing via accelerometer data, and (3) other biometric recognition authentication techniques.

## 2.1 Gesture & Motion Recognition on a Single Device

Several efficient gesture-recognition algorithms already exist. Jiayang et al. [9, 10] presented an algorithm called uWave that is based on a single accelerometer. uWave quantizes the acceleration data to reduce computational load and uses dynamic time warping to measure similarities between two time series of accelerometer data. Template adaptation deals with gesture variation over the time. Ahmad and Shahrokh [1] also proposes a gesture recognition system that uses only one 3-axis accelerometer. The system temporally compresses the acceleration time series to filter out variations not intrinsic to the gesture itself and reduces the size of the acceleration signals for next step of dynamic time warping. Then, the system uses affinity propagation to find a good set of exemplars from all data points. Finally, they implemented compressive sensing to recognize a repetition of a gesture.

For the best user experience, gesture recognition should be in real-time and easy to use. Instead of using a button to indicate start time and end time of a gesture motion, Zoltan [12] proposes an automatic segmentation method and uses two classification algorithms: Hidden Markov Models and Support Vector Machine to give high accuracy. This system has great performance and low response time, thus a good model for IoT devices.

## 2.2 Device Pairing via Accelerometer Data

In addition to recognition of a gesture, gesture-detection can also be used as a form of multifactor authentication to pair two separate devices together. Hinckley proposed one of the earlier forms of synchronous gesture authentication. By detecting an impulse when two tablets are pushed together, Hinckley pairs the two tablets, allowing the user to tile both devices together as one large screen [6]. Vinteraction uses a combination of accelerometer and vibrator data to transmit private data between two devices in physical contact. The vibrations serve as the secret shared channel between the two devices [15]. Mayrhofer et. al. have a user hold two mobile devices and shake randomly to establish a shared secret key. The shaking motion produces enough entropy to create a key that is difficult to predict [11].

Jiang et. al. propose near-field vibration (NFV) to group multiple devices together at once. By propagating the vibrations of a smartphone through a table on which all group devices are placed, the smartphone can automatically pair with all of the devices in the group [8].

In a non-security based scenario, Duet explores combining sensor information for both a smartphone and a paired watch to create more sophisticated controls based on hand gestures [4].

## 2.3 Other Biometric Recognition Authentication Techniques

Besides motion and gesture, various biometric characteristics could also be used for recognition as Jain et al. [7] specified. These characteristics include: DNA, ear, face, facial thermogram, hand thermogram, hand vein, fingerprint, gait, hand geometry, iris, palmprint, retina, signature, and voice. In some applications, biometric traits are further exploited for machine-to-machine recognition authentication instead of conventional personal recognition.

One example of this idea is an authentication scheme

based on heartbeat data (ECG) proposed by Rostami et al. [13]. It requires that the controller of implantable medical devices (IMDs) contacts the patient's body to control the IMD. Specifically, the controller can only gain access to IMDs if the ECG readings on the both devices are approximately the same.

Furthermore, a patent [2] submitted by Apple Inc. depicts a more general authentication scheme using biometric data for wireless pairing and communication between devices. The scheme is simply based on the comparison of biometric data which received and stored by the device or the host. Thus, it is applicable with any sort of distinctive biometric traits for machine-to-machine authentication once they embed related module targeting to any specific trait on their commercial devices.

## 3. REFERENCES

- [1] A. Akl and S. Valaee. Accelerometer-based Gesture Recognition via Dynamic-time Warping, Affinity Propagation, & Compressive Sensing. In *Acoustics Speech and Signal Processing (ICASSP), 2010 IEEE International Conference on*, Dallas, USA, March 2010.
- [2] Apple Inc. Wireless Pairing and Communication Between Devices Using Biometric Data. *US Patent US 20140068725 A1*, Mar 2014.
- [3] J. G. Casanova, C. S. Avila, A. de Santos Sierra, G. B. del' Pozo, and V. J. Vera. A Real-Time In-Air Signature Biometric Technique Using a Mobile Device Embedding an Accelerometer. In *Proceedings of the Conference on Networked Digital Technologies, Communications in Computer and Information Science*, Prague, Czech Republic, Jul 2010.
- [4] X. A. Chen, T. Grossman, D. J. Wigdor, and G. Fitzmaurice. Duet: Exploring Joint Interactions on a Smart Phone and a Smart Watch. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '14)*, New York, NY, 2014.
- [5] Cisco Systems, Inc. Securing the Internet of Things: A Proposed Framework. <http://www.cisco.com/c/en/us/about/security-center/secure-iot-proposed-framework.html>. (Accessed: 2016-02-16).
- [6] K. Hinckley. Synchronous Gestures for Multiple Persons and Computers. In *Proceedings of the Symposium on User Interface Software and Technology (UIST '03)*, Vancouver, Canada, 2003.
- [7] A. K. Jain, A. Ross, and S. Prabhakar. An Introduction to Biometric Recognition. *IEEE Transactions on Circuits and Systems for Video Technology*, 14(1):4–20, Jan 2004.
- [8] Z. Jiang, J. Han, W. Xi, and J. Zhao. NFV: Near Field Vibration Based Group Device Pairing. In *Proceedings of the International Conference on Collaborative Computing: Networking, Applications, and Worksharing (CollaborateCom '15)*, Wuhan, China, Nov 2015.
- [9] J. Liu, L. Zhong, J. Wickramasuriya, and V. Vasudevan. User Evaluation of Lightweight User Authentication with a Single Tri-axis Accelerometer. In *Proceedings of the International Conference on Human-Computer Interaction with Mobile Devices and*

*Services (MobileHCI '09)*, Bonn, Germany, Sep 2009.

- [10] J. Liu, L. Zhong, J. Wickramasuriya, and V. Vasudevan. uWave: Accelerometer-based Personalized Gesture Recognition and Its Applications. *Pervasive and Mobile Computing*, 5(6):657–675, Dec 2009.
- [11] R. Mayrhofer and H. Gellersen. Shake Well Before Use: Authentication Based on Accelerometer Data. In *Proceedings of the International Conference on Pervasive Computing and Communications (PerCom '07)*, Toronto, Canada, May 2007.
- [12] Z. Prekopcsák, P. Halácsy, and C. Gáspár-Papanek. Accelerometer Based Real-Time Gesture Recognition. In *Proceedings of the 12th International Student Conference on Electrical Engineering*, Prague, Czech Republic, May 2008.
- [13] M. Rostami, A. Juels, and F. Koushanfar. Heart-to-heart (H2H): Authentication for Implanted Medical Devices. In *Proceedings of the SIGSAC Conference on Computer and Communications Security (CCS '13)*, Berlin, Germany, Nov 2013.
- [14] R. Xu, S. Zhou, and W. J. Li. MEMS Accelerometer Based Nonspecific-User Hand Gesture Recognition. *IEEE Sensors Journal*, 12(5):1166 – 1173, Sep 2011.
- [15] T. Yonezawa, J. Nakazawa, and H. Tokuda. Vinteraction: Vibration-Based Information Transfer for Smart Devices. In *Proceedings of the International Conference on Mobile Computing and Ubiquitous Networking (ICMU '15)*, Hakodate, Japan, Jan 2015.
- [16] Z.-K. Zhang, M. C. Y. Cho, and S. Shieh. Emerging Security Threats and Countermeasures in IoT. In *Proceedings of the Symposium on Information, Computer and Communications Security (ASIA CCS '15)*, Singapore, Apr. 2015. ACM.