UniverSense: IoT Device Pairing through Heterogeneous Sensing Signals

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ABSTRACT

Easily establishing pairing between Internet-of-Things (IoT) devices is important for fast deployment in many smart home scenarios. Traditional pairing methods, including passkey, QR code, and RFID, often require specific user interfaces, surface's shape/material, or additional tags/readers. The growing number of low-resource IoT devices without an interface may not meet these requirements, which makes their pairing a challenge. On the other hand, these devices often already have sensors embedded for sensing tasks, such as inertial sensors. These sensors can be used for limited user interaction with the devices, but are not suitable for pairing on their own.

In this paper, we present *UniverSense*, an alternative pairing method between low-resource IoT devices with an inertial sensor and a more powerful networked device equipped with a camera. To establish pairing between them, the user moves the low-resource IoT device in front of the camera. Both the camera and the on-device sensors capture the physical motion of the low-resource device. *UniverSense* converts these signals into a common state-space to generate fingerprints for pairing. We conduct real-world experiments to evaluate *UniverSense* and it achieves an F1 score of 99.9% in experiments carried out by five participants.

HotMobile '18, Tempe , AZ, USA

DOI: 10.1145/3177102.3177108

CCS CONCEPTS

•**Networks** →*Cyber-physical networks;* •**Computer systems organization** →*Embedded and cyber-physical systems;*

KEYWORDS

Internet-of-Things, Heterogeneous sensing, Pairing

ACM Reference format:
Shijia Pan, Carlos Ruiz, Jun Han, Adeola Bannis, Patrick Tague, Hae Young Noh, and Pei Zhang. 2018. *UniverSense*: IoT Device Pairing through Heterogeneous Sensing Signals. In *Proceedings of 19th International Workshop on Mobile Computing Systems & Applications, Tempe , AZ, USA, February 12–13, 2018 (HotMobile '18),* 6 pages.
DOI: 10.1145/3177102.3177108

1 INTRODUCTION

The Internet-of-Things (IoT) requires a configured network to perform sensing and actuation tasks. Pairing is a common way to configure the network by authorizing a device with a specific MAC address to transmit on the network. With the rapid growth of IoT devices in the smart home environment, each user will have an average of over 13 devices by 2020, inevitably some will have significantly more [19]. Various pairing methods have been explored to allow easy and fast network setup, including passkeys, QR codes, and RFID tags, and each has their limitations. For example, passkey-based methods require I/O hardware such as a display and a keypad [3]. QR-code based methods require the device to have a flat surface to print or glue the QR code on. In addition, they limit the device to using a static MAC address, which may cause unexpected consequences for user privacy [15]. RFID-based methods require additional hardware to conduct pairing, such as tags and readers [24].

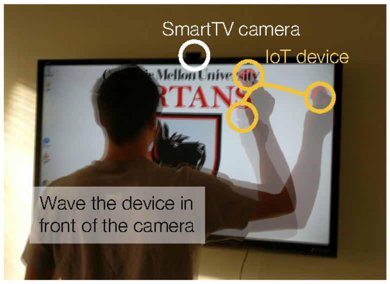

Figure 1: *UniverSense* pairing concept.

However, more and more IoT devices are designed with no interface [16, 21], which makes it difficult, if not impossible, to conduct the traditional device pairing methods [9]. Research has been done on utilizing existing on-device sensors to achieve pairing via detecting co-sensed events. They mainly fall into two categories: interaction-free and interaction-based methods. Interaction-free methods rely the fact that co-presented devices can sense events occurring in the shared physical world [17, 29]. They require no human interaction to establish the pairing between devices in the environment. However, this process usually takes a long time, especially when the frequency of detected events is low, as there is less opportunity to correlate co-sensed events. Interaction-based methods leverage human intention to designate pairing devices [13, 22, 28]. The state-of-the-art approaches require either a designated device [22] or the devices on both ends to be moved together to generate fingerprints [13], which is difficult for pairing between devices of various sizes.

We present *UniverSense*, an alternative pairing solution that enables network setup of IoT devices without an interface, by using their existing sensors. Our solution targets at the pairing between 1) interactive IoT devices (*e.g.,* smart TVs[25]), which already have I/Os, camera, and network connection, and 2) IoT devices with Inertial Measurement Units (IMU) and no interfaces [16, 21]. Figure 1 shows a concept scenario where a user moves an IoT device in front of the smart TV camera to conduct pairing. Both the camera and the IoT device itself sense the motion of the IoT device. It is challenging to extract information comparable enough for pairing from the 2-D image signal and the 3-D inertial signal. *UniverSense* achieves this by converting the co-sensed motion to a common state space and generating fingerprints for pairing. The contributions of this work include:

- We introduce an IoT device pairing mechanism, *UniverSense*, that allows devices with different sensing modalities to pair through motion sensing.
- We present a fingerprint generating and pairing method for heterogeneous sensing signals that extracts shared physics representations of the motion from sensors of different modalities.
- We conducted real-world experiment to evaluate our pairing mechanism.

The rest of the paper is organized as follows. Section 2 introduce our pairing mechanism *UniverSense*. Then, we evaluate *UniverSense* through real-world experiments in Section 3. Next, we discuss the potential expansion of this work in Section 4. Finally, we compare this work with related work in Section 5 and conclude in Section 6.

2 *UNIVERSENSE* SYSTEM OVERVIEW

UniverSense pairs devices based on detecting shared physical motion. Figure 2 shows the pairing process. *UniverSense* first obtains the motion signals (Section 2.1), which are observed by each device involved in the pairing. Then, *UniverSense* converts each motion signal –detected by different sensor modalities– into a common state space (Section 2.2). Next, each device generates a fingerprint based on the converted signal (Section 2.3). Finally, the fingerprints are used to determine whether a successful pairing should be established (Section 2.4).

2.1 Heterogeneous Sensing

The heterogeneity of the pairing devices allows the more 'powerful' IoT devices (*i.e.,* computational power, sensors, interface, network) to complement the low-resource IoT device with no interface, allowing for pairing between them and potentially to the rest of the home network. The 'powerful' devices include 1) interactive devices, such as smart TVs equipped with camera(s) to enable user interaction [25] and 2) ambient sensing devices, such as security cameras [12]. These cameras capture image frames that contain the position/movement of the IoT device. On the other hand, low-resource IoT devices are likely to be equipped with an IMU [16, 21]. An IMU consists of an accelerometer, a gyroscope and a magnetometer, which measure the linear acceleration, the rotation rate of the device, and the magnetic field respectively in body coordinates of the IoT device. We assume that in this paper the low-resource IoT device has IMU internally.

2.2 Conversion to a Common State-Space

The challenge of heterogeneous sensing-based pairing is that the measured signals are in different sensing state-spaces and therefore cannot be directly compared. However, if a user moves the low-resource IoT device in front of the camera, both sensors can obtain common information about the motion (in the form of position, acceleration, etc.) of the low-resource IoT device **in world coordinates** (*i.e.,* with respect to *down* and *North*). Integration or differentiation could transform acceleration and position into a common magnitude. In this regard, the literature is unanimous with respect to avoiding integration of acceleration signals measured on devices that can move freely in space [7, 18]. Integration is unsuitable for two main reasons that cause the error to accumulate faster than linearly over time: the propagation of the error in the orientation estimate (which is used to remove gravity from the raw acceleration) and the drift induced by

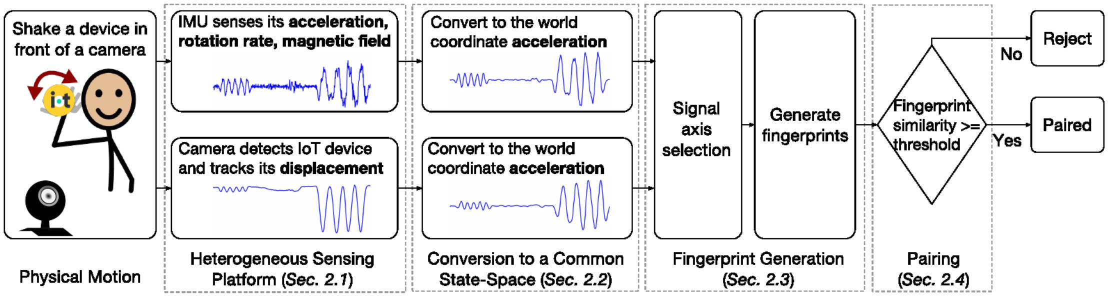

Figure 2: *UniverSense* system overview.

integration of noisy signals. Therefore, we use differentiation to convert displacement into acceleration, and define the **world coordinates acceleration** as the common state-space of our camera-IMU sensor pair.

2.2.1 Converting IMU signal to device acceleration. To obtain the acceleration of IMU in world coordinates, *UniverSense* estimates the device orientation from a 9-axis IMU signal and projects the raw acceleration readings to a global frame of reference. This process basically consists of obtaining a rotation matrix ${}^{W}_{B}R$ that converts **B**ody coordinates into **W**orld coordinates. Then, *UniverSense* utilizes ${}^{B}_{W}R$=i${}^{W}_{B}R^{-1}$ to project *gravity* into body coordinates so it can be removed from the raw acceleration signal. Finally, the result is expressed in world coordinates by multiplying by ${}^{W}_{B}R$ [18].

2.2.2 Converting camera stream to device acceleration. To extract the acceleration of the low-resource IoT device, *UniverSense* first detects the device from the video stream, then calculates the position of the device, and finally converts the position into acceleration. Object *detection* methods take a still image as the input, and provide a set of pixel coordinates for each target found [1, 8]. Then, object *tracking* processes the detection on consecutive frames and assigns a common ID to each target found in both images. Finally, the position of the IoT device can be tracked over time by converting pixel coordinates to the world frame. This conversion requires knowledge of the camera extrinsics (*i.e.,* the camera's ${}^{W}_{B}R$, estimated through *e.g.,* an IMU or a pre-calibration) as well as intrinsics (obtained from the manufacturer) [30]. Once the camera obtains the world coordinate position of the device, *UniverSense* performs a double differentiation on the estimated 3-D position of the IoT device to obtain the corresponding acceleration. In this work we assume the motion is performed perpendicular to the view of the camera at a known distance; in a real implementation, the 3-D position can be mapped into the camera view plane.

2.3 Fingerprint Generation

UniverSense generates binary fingerprints from acceleration signals to reduce the data exchanged. It takes two main steps: signal axis selection and fingerprint generation.

Signal axis selection Due to the noise of the sensor, when the motion of the device is not significant on the investigated axis, the low Signal-to-Noise Ratio (SNR) may cause low pairing success rate. *UniverSense* collects signals of all axises and selects the axis that has the highest signal energy to conduct fingerprint generation on.

Fingerprint generation *UniverSense* projects the acceleration signal into a binary signal by setting a threshold. If the absolute value of the signal is over the threshold, the bit is 1, otherwise, the bit is 0. Since the mean acceleration signal is close to 0, we specifically select an offset away from 0. With a sampling rate of 30 Hz, we estimate a 5-second motion can be used to generate a 128-bit fingerprint, and an 18-second motion can be used to generate a 512-bit fingerprint. Figure 3 shows an example of the fingerprint generated from IMU and camera measurements.

2.4 Pairing

To initiate the pairing, the 'powerful' device broadcasts a pairing request and start to generate fingerprint FP_{cam}. Once the low-resource IoT device receives the request, it starts to generate its fingerprint FP_{IMU}. Once the fingerprint reaches the designated length, the low-resource device sends its MAC address with the generated fingerprint. The 'powerful' device compares the received FP_{IMU} to its FP_{cam} and calculates the fingerprint similarity. If the two fingerprints have similarity over a threshold, *UniverSense* considers them as paired.

3 EVALUATION

We implemented *UniverSense* to evaluate our pairing method in a real-world environment (Section 3.1). We evaluate the

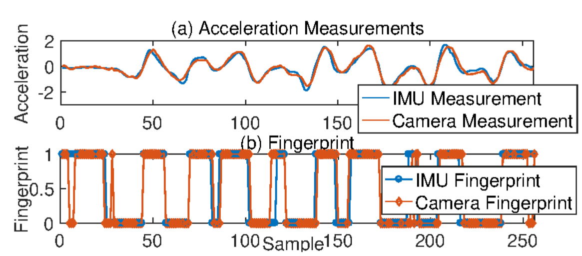

Figure 3: Fingerprint generation example.

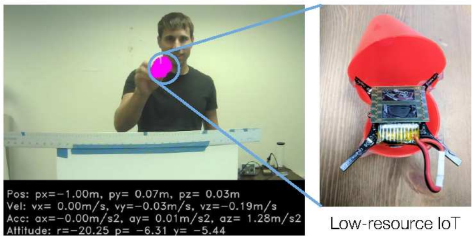

Figure 4: Experiment settings (camera view).

motion variable (Section 3.2) and pairing performance (Section 3.3) respectively.

3.1 Implementation

To evaluate *UniverSense*, we conducted real-world experiments with an off-the-shelf RGB camera (ELP 3.0 MegaPixel USB camera) for the 'capable' device, and IMU device from an IoT sensing platform, CrazyFlie 2.0, as the 'low-resource' device [4]. We covered the CrazyFlie with an orange plastic cap and used a color (hue) detector in OpenCV, together with an object tracker [11] to ensure we correctly follow the target. For real use cases, a more robust object detector could easily replace the current simplified version, without requiring any hardware modifications. In order to reduce the effect of sensing noise in the visual position estimation, we obtain good results with a traditional Savitzky-Golay (also known as Least-Squares) smoothing differentiation filter [27]. On the CrazyFlie, we use the popular Madgwick orientation filter [14] to minimize the drift in the orientation estimation. Figure 4 shows our experiment setup from the camera view, where the camera is 1.5m away from the motion area. Fingerprints used in the evaluation are 512 bits.

3.2 Motion Variable Analysis

We evaluate the system feasibility to match motion accelerations measured by camera and IMU under different motion variables: amplitude and velocity. We fix one parameter when evaluating the other. We asked one participant to conduct a designated motion 10 times and demonstrate the similarity of the pairwise fingerprints from camera and IMU.

3.2.1 Motion amplitude. We evaluate four different motion amplitudes, including 10, 20, 40, and 80 cm, with the motion velocity fixed. We control the motion velocity by asking the participant to conduct the motion of designated length within a given duration. We plot the fingerprint similarity against motion amplitude in Figure 5 (a). When the motion amplitude is 20 cm, the system achieves highest fingerprint similarity 0.95. When the motion amplitudes are 40 and 80 cm, the average fingerprint similarity drops below 0.9. The reason is that when the motion is in a large range, the velocity change is relatively small during the motion, and therefore the acceleration signal amplitude is low.

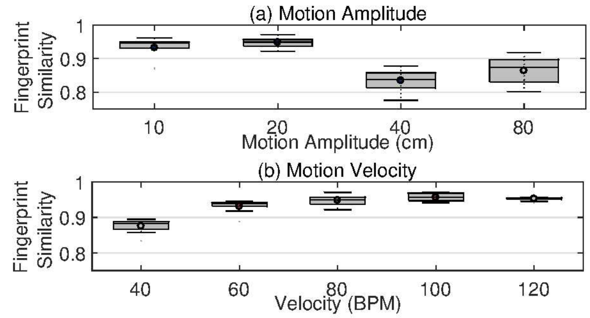

Figure 5: Motion variables' effect on fingerprint similarity. (a) shows the effects of motion amplitude. (b) shows the effect of motion velocity.

3.2.2 Motion velocity. Since *UniverSense* projects different sensing modalities into acceleration, the motion velocity affects the acceleration signal amplitude. We mainly investigate 5 different motion velocities controlled by metronome beats: 40, 60, 80, 100, 120 beats per minute (BPM) with a motion amplitude of 20 cm. We demonstrate the fingerprint similarity against motion velocities in Figure 5 (b). We observe an increasing trend of the fingerprint similarity for velocities lower than 80 BPM. However, when the velocity increases above 80 BPM, the increase of the motion velocity has little effect on the fingerprint similarity.

3.3 Pairing Performance

We further evaluate the pairing performance from two aspects: 1) human factors, and 2) the efficiency of fingerprints. We first investigate the human factor by asking multiple people to conduct experiment and evaluate the robustness of *UniverSense* through different users. Then we evaluate the fingerprint efficiency by analyzing the fingerprint similarity of the same motion and across different motions, and the pairing success rate with a selected pairing threshold.

3.3.1 Human factors. Different people may perform pairing motions differently. Therefore, we conduct experiments with multiple users and ask them to move the IoT device within a designated area (a circle of 45 cm radius) arbitrarily for 20s. We compare multiple users' pairing fingerprint similarity calculated from different signal axises to demonstrate the system robustness, and the results are shown in Figure 6. The average fingerprint similarity across 5 participants using X-axis, Y-axis, and our axis-selection approach are respectively 0.845, 0.915, and 0.917, with standard deviations of 0.146, 0.038, and 0.036. Our approach achieves the highest fingerprint similarity and demonstrates stable matching performance. This is because different people may come up with different pairing motions. If a fingerprint is generated using an axis that lacks significant movement, the SNR will be low, giving a low fingerprint similarity. Our approach uses the axis with the highest SNR among the available signal axises to achieve high fingerprint similarity.

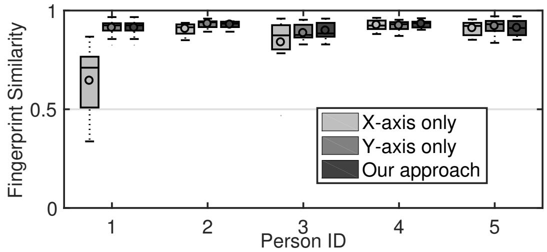

Figure 6: Different signal axes' fingerprint similarity.

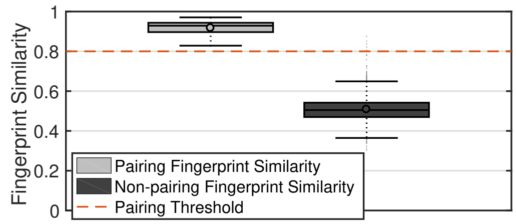

Figure 7: Compare fingerprint similarity of the same motion v.s. of different motions.

3.3.2 Fingerprint similarity analysis. We further analyze the fingerprint similarity between camera and IMU signals originating from world coordinate acceleration of the same motion, versus those from different motions and show it in Figure 7. The fingerprint similarity of the same motion, even detected by sensors of different modalities, is often over 0.8, which we set as the **pairing threshold**. On the other hand, the fingerprint similarity across different motions are relatively low, with an average of around 0.5. This indicates the feasibility of our system. We consider a successful pairing when the fingerprint similarity between the camera and an IMU device is above the pairing threshold. With a threshold of 0.8, the system achieves a precision of 100%, a recall of 99.8%, and an F1 score of 99.9% in 50 trials.

4 DISCUSSION

The previous section demonstrated the feasibility of our pairing mechanism. Here we discuss some limitations and potential extensions of this work.

4.1 Secure Pairing through *UniverSense*

UniverSense provides efficient device pairing for low-resource IoT devices that do not have a direct interaction I/O. On the other hand, establishing secure network is very important considering the growing number of IoT devices. Compared to current scan-based pairing, *e.g.,* Samsung SmartThings [26], fingerprints generated by *UniverSense* can be used to establish shared keys for secure pairing. Prior work has been done to achieve secure pairing through protocols that utilize similar fingerprints generated from the sensing of shared physical events for IoT devices and vehicles [10, 17]. The challenges for secure pairing through *UniverSense* include designing a pairing protocol that can effectively defend against attacker models (*e.g.,* eavesdropping, Man-in-the-Middle).

4.2 Object Recognition and Auto-Pairing

The implementation of this work relies on color markers to recognize the IoT device and a fixed depth to track its motion. Various work has been done on object recognition, single camera depth estimation, and human motion tracking [5, 23]. With these trending new approaches for robust object recognition and tracking, we believe the pairing can be done without intentionally moving the device. The camera can capture the motion of the device or human hand whenever the human interacts with it, and then link the physical objects/device to their virtual ID.

5 RELATED WORK

Device pairing has been explored using various sensing approaches. Traditional methods include passkey, QR code, and RFID, all of which face certain sensing limitations. Passkey-based methods require I/O hardware such as a display and a keypad [3]. QR-code based methods require either a flat surface or a screen to show the QR-code [2], but either case requires specific types of surfaces that certain devices may not meet. RFID relies on tags and readers specifically used for pairing [24], adding unnecessary hardware. These traditional methods do not apply to our problem because the type of low-resource IoT devices we focus on in this paper does not have I/O or extra hardware.

Sensing shared physical phenomena through co-presented devices has been applied under different scenarios to tackle these limitations. These methods mainly fall into two different categories: context-based and interaction-based. **Context-based pairing** methods generally utilize everyday events that can be detected by co-presented sensors [17, 31]. These methods often require zero-interaction and establish the secured network automatically. However, due to the randomness of human activities, this process can take a very long time (*e.g.,* days) to identify the shared context.

Interaction-based pairing methods often utilize human intention to designate pairing devices, such as shared motions induced by human activities [13, 28] or pointing to the targets [22]. Involving human interaction leads to reduced pairing times (*e.g.,* seconds). However, the state-of-the-art either requires a specific device, the 'wand' [22] or provides this type of pairing when the same motion is applied to both devices simultaneously [13, 28], thus limiting the variety of devices that can be paired (*e.g.,* shaking a smart TV with an IoT device might be difficult). *UniverSense* provides an alternative flexible pairing through conversion of multi-modal sensing signals, which allows the pairing between IoT devices of heterogeneous systems without additional devices.

Prior work has been done utilizing sensors of different modalities to achieve various sensing tasks. Nguyen et al. combine camera and Wi-Fi signals to localize and identify people in an indoor environment while they carry their smartphones [20]. Chen et al. utilize inertial and depth sensors to accurately link the detected motion on both devices and use this information to estimate the fitness of seniors [6]. Among these multi-modal sensing applications, to the best of our knowledge, we are the first to apply the shared physical-phenomena detected by sensors of different sensing modalities on device pairing.

6 CONCLUSION

In this paper, we present *UniverSense*, a multi-modal sensing based pairing method that pairs 'powerful' devices equipped with a camera to low-resource IoT devices with no interface. The user moves the low-resource IoT device in front of the camera so that the camera can capture the device motion. The low-resource IoT device, on the other hand, measures its own motion through its embedded IMU. These sensed motion signals are then converted into a common state-space to generate pairing fingerprints. We evaluate *UniverSense* through real-world experiments with multiple participants, and it achieves a 99.9% F1 score for the pairing success rate.

ACKNOWLEDGEMENTS

This research was supported in part by the National Science Foundation (under grants CNS-1149611, CMMI-1653550 and CNS-1645759), Intel and Google. The views and conclusions contained here are those of the authors and should not be interpreted as necessarily representing the official policies or endorsements, either express or implied, of CMU, NSF, or the U.S. Government or any of its agencies.

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