BeeHIVE: Behavioral Biometric System Based on Object Interactions in Smart Environments

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Abstract: The lack of standard input interfaces in Internet of Things (IoT) ecosystems presents a challenge in securing such infrastructures. To tackle this challenge, we introduce a novel behavioral biometric system based on naturally occurring interactions with objects in smart environments. This biometric leverages existing sensors to authenticate users without requiring any hardware modifications of existing smart home devices. The system is designed to reduce the need for phone-based authentication mechanisms, on which smart home systems currently rely. It requires the user to approve transactions on their phone only when the user cannot be authenticated with high confidence through their interactions with the smart environment. We conduct a real-world experiment that involves 13 participants in a company environment. We show that this system can provide seamless and unobtrusive authentication while still remaining highly resistant to zero-effort, video, and in-person observation-based mimicry attacks. Even when at most 1% of the strongest type of mimicry attacks are successful, our system does not require the user to take out their phone to approve legitimate transactions in more than 84% of cases for a single interaction. This increases to 93% of transactions when interactions with more objects are considered.

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1 INTRODUCTION

The growing number of smart devices that are incorporated into smart environments leads to a wider presence of a variety of sensors. These sensors can be leveraged to improve the security of such environments by providing essential input about user activities. In many environments, the control over specific devices or financial transactions should only be available for an authorized group of users. For example, smart windows in a child's bedroom should not open when the parent is not present, and the child should not be able to order hundreds of their favorite candy bars using a smart refrigerator. Similarly, not all office workers should have access to a smart printer's history, nor should the visitors in a guesthouse be able to change credentials on smart devices that do not belong to them. But while there is a need for authentication, smart devices offer limited interfaces for implementing security measures. This can be mitigated by requiring that the user initiates or approves every transaction through a privileged companion app running on the user's smartphone. However, this can be very cumbersome as the user needs to have their phone at hand and thus negates many advantages that smart environments offer in the first place.

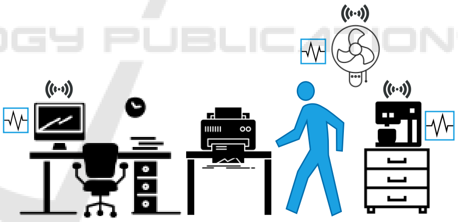

Figure 1: An overview of the *BeeHIVE* system. As the user interacts with the printer, sensors embedded in smart objects surrounding the user and the printer record these interactions. Physical signals generated from the user's movements are picked up by sensors such as accelerometers, pressure sensors and microphones, and are used to profile them. The system authenticates the user before allowing them to perform certain actions, such as payments.

On-device sensors such as microphones, passive infrared (PIR) sensors, and inertial measurement units (IMUs) have been extensively used to recognize different activities performed by users in the area of Human Activity Recognition (HAR) (Irvine et al., 2020). Prior work has focused on using one type of input data to authenticate users, such as voice, breath, heartbeats or gait (Saleema and Thampi, 2018; Meng et al.,

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2018; Chauhan et al., 2018; Sun et al., 2018; Barros et al., 2019).

Several systems that rely on diverse types of inputs have been proposed to make attacks more difficult (Abate et al., 2011; Castiglione et al., 2017; Maček et al., 2016; Olazabal et al., 2019; Cherifi et al., 2021). While these approaches are promising, they often do not utilize the full potential of co-located heterogeneous devices in smart environments. In this paper, we propose the *BeeHIVE* system that uses sensor data collected during day-to-day interactions with physical objects to implicitly authenticate users without requiring users to change smart home hardware or adapt their behavior. This system can be used to complement phone-based authentication methods that require users to explicitly approve transactions through privileged apps. By using *BeeHIVE* together with a phone-based authentication method as a fallback, smart environments can become more seamless and unobtrusive for users without sacrificing their security.

We conducted a 13-person experiment in a company environment to validate the performance of *BeeHIVE* and explore the effectiveness of imitation attacks. The proposed technique is assessed in three modes of operation to use (1) features from sensors placed on the object with which the user interacts, (2) features only from sensors on co-located objects, and (3) features from both on-device and co-located sensors. Overall, our analysis proves that the system achieves desirable security properties, regardless of the amount of smart office users or the environment configuration. We make the following contributions in the paper:

- We propose a novel biometric based on interactions with physical objects in smart environments.
- We collect a 13-person dataset in a company setting to evaluate the authentication performance of the proposed system.
- We make all data and code needed to reproduce our results available online [1].

2 BACKGROUND AND RELATED WORK

Existing biometric authentication systems that utilize data collected from mobile and smart devices are generally categorized into single-biometric or multi-biometric approaches (Castiglione et al., 2017; Abate et al., 2011; Yang et al., 2021). The systems from the first category collect inputs of a specific type (e.g., sounds, images, acceleration readings) and search for unique patterns. On the other hand, multi-biometric systems combine the data extracted from multiple sources to create unique signatures based on different sensor types. Such systems are less prone to mimicry attacks due to the complexity of spoofing multiple modals simultaneously (Yampolskiy, 2008).

Single-Biometric Systems. The vast majority of existing commercial and non-commercial systems used in smart environment contexts (Barra, 2013; Saleema and Thampi, 2018; Meng et al., 2018; Blue et al., 2018) primarily rely on voice recognition to authenticate users. Since these systems are often vulnerable to voice spoofing and hijacking attacks (Carlini et al., 2016; Zhang et al., 2017; Diao et al., 2014; Zhang et al., 2018), research efforts shifted towards hardening voice recognition systems by leveraging anti-spoofing mechanisms like proximity detection or second factors (Blue et al., 2018; Meng et al., 2018).

The built-in sensors of IoT devices also enable the use of more unconventional traits, such as breathing acoustics (Chauhan et al., 2018), heartbeats (Barros et al., 2019), gait or human body movements (Musale et al., 2018; Sun et al., 2018; Musale et al., 2019; Batool et al., 2017) in smart environments.

Multi-Biometric Systems. To improve adaptability and accuracy of single-biometric systems, various multi-biometric systems have been proposed (Abate et al., 2011; Castiglione et al., 2017; Kim and Hong, 2008; Maček et al., 2016; Gofman et al., 2018; Cherifi et al., 2021). For example, Olazabal et al. (Olazabal et al., 2019) proposed a biometric authentication system for smart environments that uses the feature-level fusion of voice and facial features. These solutions, however, still require users to actively participate (e.g. by shaking devices or repeating specific hand wave patterns) in the authentication process and rely on the presence of specific sensors in the smart environment. To address such limitations, the MUBAI system (Abate et al., 2011) employs multiple smart devices to extract various behavioral and contextual features based on well-known biometric traits such as facial features and voice recognition.

Interaction-Based Biometric Systems. Such systems have been widely discussed for mobile platforms (Teh et al., 2016). Typically, on-device sensors are employed to measure touch dynamics or user gestures (Tafreshi et al., 2017; Lee et al., 2017; Ellavarason et al., 2020; Shrestha et al., 2016; Sturgess et al., 2022; Verma et al., 2022). For example, users can be profiled based on how they pick up their phones or how they hold them (Attaullah et al., 2016). Similar techniques have been used in smart environments (Al-

[1] https://github.com/ssloxford/beehive

mohamade et al., 2021); however, most of the existing solutions not only require the user to actively participate in the authentication process but also rely on a specific setup. Our goal is to introduce a biometric system that continuously and seamlessly authenticates the users while they are interacting with the devices around them without restrictions on sensor placement.

SenseTribute. Closest to our work is SenseTribute (Han et al., 2018), which performs occupant identification by extracting signals from physical interactions using two on-device sensors—accelerometers and gyroscopes. Its main objective is to attribute physical activities to specific users. To cluster such activities, SenseTribute uses supervised and unsupervised learning techniques, and segments and ensembles multiple activities. There is a palpable risk in real-world smart environments that users will attempt to execute actions that they are not authorized for. This requires means for not just identification, but also authentication. Therefore—in contrast to SenseTribute, which focuses on user identification—the main objective of our system is user authentication, for which we conduct a more extensive experiment evaluating various types of active attacks. In office and home environments, it is easy for anyone to observe interactions made by authorized users, and it is natural that, for example, kids may seek to imitate their parents. Going beyond previous work, we therefore evaluate the robustness of our system against mimicry attacks based on real-time observation or video recordings.

Furthermore, SenseTribute expects all objects to be equipped with sensors. Yet, this is not always a realistic assumption, as sensors are often deployed only near (but not on) interaction points. Thus, we propose a system that uses nearby sensors present in co-located IoT devices to authenticate user interactions.

3 SYSTEM DESIGN

Figure 1 shows an overview of the system design. The proposed *BeeHIVE* system is meant to complement existing app-based authentication mechanisms used to secure current smart home platforms. Our system authenticates the user through their interactions with the smart environment and only requires the user to approve transactions through the app as a fallback if it cannot authenticate the user with confidence itself. This way, *BeeHIVE* can reduce the reliance on these app-based authentication mechanisms without compromising on the security of the smart home platform.

3.1 Design Goals

In order to support the system design and evaluation methodology, we define the following design goals:

Unobtrusiveness. The system should not require users to perform explicit physical actions for the purpose of authentication nor require them to modify their usual behavior.

Low False Accept Rate. As the system is designed to be used alongside app-based authentication, it should prioritize low false accept rates to avoid significantly weakening the security of the overall smart environment system.

Low Friction. The system should provide a seamless experience to the user wherever possible. This means that false reject rates should be kept low to reduce the need of falling back on the usual app-based authentication of the underlying smart environment platform. However, this should not come at the cost of higher false accept rates.

No Restrictions on Sensor Placement. The system should use data from existing sensors without making restrictions on their placement or orientation. This ensures that the system can be applied to existing deployments purely through software. In addition, the system should not require sensors on each object but instead use sensors on other nearby devices.

Robustness to Imitation Attacks. Due to the ease of observation in home environments, the system's error rates should not increase significantly even when subjected to imitation attacks.

3.2 System Model

In this paper, we consider smart environments where objects such as fridges or cupboards are augmented by smart devices that monitor their state and provide access to enhanced functionality. People naturally interact with many of these smart objects during their daily activities. Each activity consists of a set of tasks. For instance, to prepare a meal, a user has to walk to the fridge and open it to collect ingredients. The user then has to walk to the cupboard to pick up the plates. Behavioral data of these tasks are measured with different types of sensors with which smart devices are frequently equipped. As some objects might not have any suitable sensors attached to them, we also consider nearby sensors to profile object interactions. This is particularly true for physical objects without smart capabilities (e.g., cupboards or drawers). In order to illustrate these different possible deployment settings, we consider three system configurations:

- ON-OBJECT, where sensors are mounted directly on the object
- OFF-OBJECT, where only co-located sensor data are considered
- COMBINED, which uses sensor data of both the device on the object as well as from co-located devices

We use sequences of interactions to increase confidence in system decisions. This way, the user can be better authenticated if they perform several tasks in succession. As a simplification, we focus on authenticating one user at a time and do not consider multiple users interacting with objects simultaneously. It is important to note that in our system a failed authentication does not mean that the user is barred from making transactions. Instead, they are required to use their phone to approve the requested transaction.

3.3 Adversary Model

An adversary's ($\mathcal{A}$) main objective is to convince the smart environment that they are a legitimate user (U_L). Such a misclassification can result in permitting $\mathcal{A}$ to execute on-device financial transactions or any other types of sensitive operations on behalf of U_L. We assume that $\mathcal{A}$ has physical access to the environment, but is otherwise an unprivileged user such as a child or a visitor. Moreover, $\mathcal{A}$ cannot tamper with the smart devices by, for example, connecting to the debug port to flash the device firmware. We also assume that smart devices and the user's smartphone are not compromised; thus, they can be considered a reliable data source. Based on these assumptions, we also exclude the possibility of the attacker interrupting the training phase, which could result in the generation of incorrect biometric signatures of authorized users.

In order to achieve their goal, $\mathcal{A}$ may attempt to mimic the behavior of U_L to generate a matching biometric fingerprint. Successful mimicry attacks on various biometric systems have been previously demonstrated (Khan et al., 2018). In our scenarios, we consider three types of such attacks: (1) zero-effort attackers who interact with the environment naturally without attempting to change their behavior, (2) in-person attacks in which $\mathcal{A}$ can observe legitimate users interacting with IoT devices in person, and (3) video-based attacks in which $\mathcal{A}$ possesses a video recording of the user interacting with the IoT devices in a smart environment. While in-person attacks give $\mathcal{A}$ a chance to inspect U_L's interactions more closely and potentially capture more details, recordings can provide additional time to learn U_L's behavior.

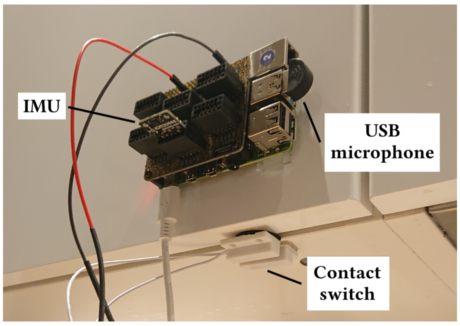

Figure 2: Raspberry Pi on a kitchen cupboard. The contact switch detects the opening and closing of the cupboard; the microphone and the IMU record sensor measurements of the interaction.

4 EXPERIMENTAL DESIGN

In order to evaluate the feasibility of authenticating users seamlessly based on their interactions with smart devices, we conducted an experiment in a smart office environment with thirteen participants. This experiment is further used to study attackers that attempt to copy the behavior of the legitimate user to execute mimicry attacks.

Data Collection. For our experiment, we collected data from a wide range of typical smart home interactions using sensors similar to those already present in most smart environments. Since raw sensor data in smart devices are typically inaccessible to developers, we deploy Raspberry Pi 3 devices equipped with the same types of sensors to simulate such an environment and study object interactions. We use a total of 8 Raspberry Pi devices equipped with magnetic contact switches, USB microphones (recording sound pressure levels), and ICM20948 inertial measurement units (IMUs) (providing an accelerometer, a gyroscope, and a magnetometer) to collect the data for the experiments. The Raspberry Pi devices are fitted to typical home appliances (e.g., fridge or coffee machine) and kitchen furniture (e.g., drawers or cupboards). The magnetic contact switches are used in place of a typical type of smart office device (i.e., a door/window contact sensor) and they provide the ground truth for the occurrence of interactions with smart objects (e.g., the opening of a kitchen cupboard augmented with a contact sensor). The IMUs measure the motion sensor data from the interaction (i.e., acceleration, gyroscopic motion, and orientation) and are being polled through the I^2C interface of the Raspberry Pi devices. We note that, beyond their primary purpose, many common smart devices em-

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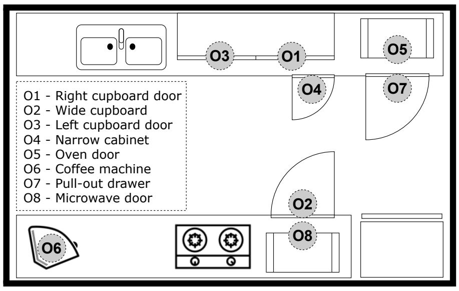


Figure 3: A simplified layout of the room and the arrangement of the objects $O1-O8$ the participants interacted with during the experiment.

ploy IMUs to protect against tampering [2]. The inputs from the USB microphones are only used to calculate sound pressure levels, but no actual audio data is being stored. See Figure 2 for an example deployment of one of our measurement devices.

Mimicry Attacks. This project has been reviewed and approved by the research ethics committee at our university, reference number CS_C1A_20_014-1. The experiment is conducted in the office kitchen of a hotel company. An overview of the deployment and the room layout are shown in Figure 3. As object interactions, we consider in this experiment: 4 cupboards, 1 mini oven, 1 pull-out drawer, 1 microwave, and 1 coffee machine. Apart from the coffee machine, all of these interactions involve the opening and closing of the doors of the interaction point. To get the ground truth for the coffee machine interaction, the user first opens a lid on top of the coffee machine which is outfitted with a magnetic contact switch. The user then proceeds with pressing buttons on the coffee machine, before they end the interaction by closing the lid on top of the machine again.

Each of the participants performs 20 runs of interactions. Then, one of the participants is randomly chosen as the legitimate user and victim of the attack. The rest of the participants are split into two groups of six attackers who can observe the user's interactions with the smart environment and try to mimic the victim's behavior. The first group can only observe the victim in-person, whereas the second group has access to video recordings of previous object interactions which they can study in their own time.

5 METHODS

In this paper, we define a task T as a physical interaction initiated by user U_L with an object O. Each task is represented by a time series, which is constructed from the data collected by on-device sensors, including microphones, accelerometers, gyroscopes, and magnetometers. This data represents the physical signal generated by the user while they interact with the smart object.

Figure 4 presents the system overview and explains its processing pipeline. Base-learners are weak classifiers that are combined to form an ensemble to facilitate the decision-making process. When the user performs a sequence of tasks on several smart objects, the system extracts the features for these tasks from on-object sensors as well as sensors in proximity. Next the features become an input to the n base-learners corresponding to those tasks—resulting in predictions P_1 to P_n. Finally, the meta-learner gathers all predictions made by all the base-learners and decides on the final prediction P_F in the second-level prediction layer. This way, a smart environment can benefit from the heterogeneous character of smart devices and their built-in sensors by performing a decision-level fusion to improve the classification accuracy.

Preprocessing. Figure 5 presents the sensor readings when U_1 interacts with the narrow cabinet during the experiment. While (a) shows the signal that the gyroscope sensor of the cabinet has captured, (b) reveals what has been registered by a co-located sensor. Co-located sensors are all sensors in proximity to an object that can capture physical signals originating from interaction with this object. The microphone on the wide cupboard recorded two events—opening and closing the door of the cabinet. These movements are part of the task T performed on smart object O. The start and end of T are time-stamped by the contact sensors and denoted as t_0 and t_1 respectively (marked with red dotted lines in Figure 5). The signals from T are segmented by the values of t_0-1 and t_1+1 before proceeding to the feature extraction phase.

Feature Extraction and Selection. For each physical interaction with an object O, the system extracts matrices with time series data for the sensor components of this object and co-located objects. This data is only extracted between t_0-1 and t_1+1. We add windows of a second to account for signals that originate from the start and end motions. We found that this time window was the most optimal for capturing initial movement without including any residual effects of other interactions. The statistical functions are computed for each column of these matrices, and are categorized into two groups: time-domain features (min, max, mean, median, std, var, kurtosis, skewness, shape factor, absolute energy, mean of central approx. of 2^{nd} derivative, mean/sum of abs. change,

[2] https://www.arrow.com/en/research-and-events/articles/mems-and-iot-applications

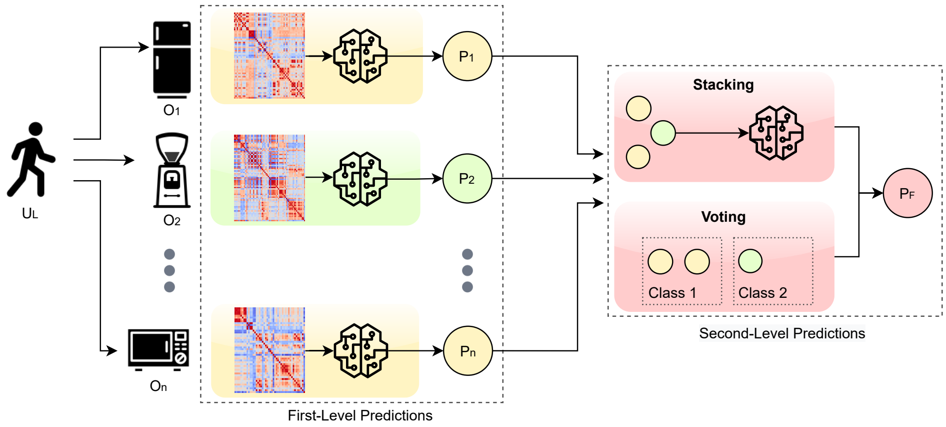
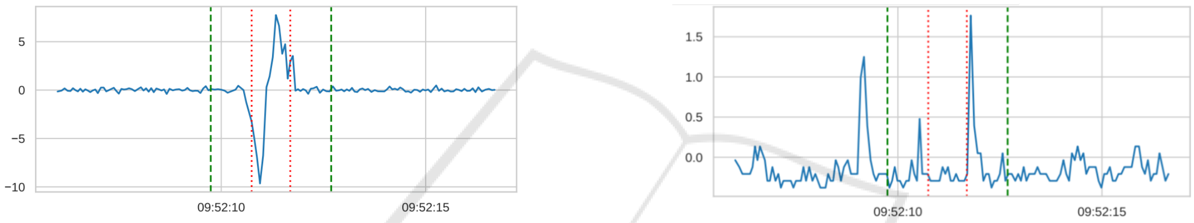


Figure 4: The diagram provides an overview of the processing pipeline of a multi-sensor fusion system. The system extracts relevant features from U_L's interactions with objects O_1 to O_n and supplies them to their base-classifiers. Then, the first-level predictions P_1 to P_n are fed into a meta-classifier (i.e., a voting or stacking classifier) that computes the final prediction P_F.



(a) An interaction measured by the x axis of O_4's gyroscope.

(b) The same interaction picked up by the microphone of the co-located O_2.

Figure 5: As users interact with smart devices, signals from on-device sensors are collected and processed by the system. Signals (a) and (b) are generated by a participant U_1 that has interacted with the narrow cabinet O_4. The wide cupboard O_2 picked up additional input from the same interaction with object O_4 as they were co-located. Red dotted lines indicate the start (t_0) and end (t_1) of the T task while the green dashed lines denote ± 1 seconds windows.

peaks) and frequency-domain features (Fourier entropy). These features help to analyze the biomechanical effect of a given interaction on physical signals and identify characteristics of movements (Rosati et al., 2018). For microphone data, we extract sound pressure levels (SPLs) instead of actual audio recordings. Thus, statistical functions are applied to SPL values. As for the feature selection process, the system selects a subset of extracted features using mutual information (MI) (Beraha et al., 2019).

Multi-Sensor Fusion. Every node in a smart environment extracts different sets of characteristics from user interactions due to their placement, purpose, and composition of built-in sensors. Various fusion approaches exist that can boost the detection accuracy and system effectiveness in multi-sensor environments (Aguileta et al., 2019). Among these fusion techniques, we focus on *decision-level methods* which allow the introduction of multiple classifiers, *base-learners*, that independently undertake a classification task. This gives a certain degree of autonomy to individual base-learners trained on specific smart object interactions. As shown in Figure 4, after each first-level base-classifier makes a prediction, the second-level meta-classifier determines the final outcome. The efficiency and effectiveness of various fusion techniques at the decision level have been extensively studied in the area of Human Activity Recognition (HAR) (Aguileta et al., 2019). While our focus is on user authentication, we hypothesize that similar approaches can be just as effective in our case. As such, we compare two ensemble learning techniques that use fundamentally different classification methods but show promise for good performance in multi-user smart environment scenarios.

Ensemble Learning. A meta-learner is trained using labels obtained from the first-layer base-learners, as its features (Wolpert, 1992). Stacking allows combining various classifiers (e.g., k-Nearest Neighbours, Random Forests, Decision Trees, etc.) using different sets of features for each. In our scenario, the biggest advantage of this approach is that the meta-classifier learns which object interactions predict labels more accurately. Voting is another ensemble learning method discussed in this paper. In comparison to stacking, this technique does not require a separate machine learning model to make final predictions. Instead, it uses the deterministic majority voting algorithm to compute the result.

6 EVALUATION

This section provides a detailed examination of the data collected during the experiment, along with an exploration of potential implications for future research.

6.1 Distinctiveness of Sensor Features

In order to judge the distinctiveness of features by different types of sensors, we use relative mutual information (RMI). RMI is a well-known measure for assessing the distinctiveness of different features because it quantifies the amount of information that one feature provides about another, while taking into account the amount of information that each feature provides individually. RMI is defined as $\mathrm{RMI}(user, F) = \frac{H(user)-H(user|F)}{H(user)}$, where H(A) is the entropy of A and H(A|B) denotes the entropy of A conditioned on B. Here, *user* denotes the ground truth of the user performing the object interaction, whereas F is the vector of extracted features.

Tables 1 and 1b show the RMI for individual sensors that have been placed on multiple objects as part of our experiment. These scores represent aggregated maximum values of RMI for a particular sensor on a specific object O_i, given different configurations of the system. Each of these objects introduces a different way for a user to interact with the smart environment. Analysis of the distinctiveness of the features extracted from these sensors allows us to understand which ones contribute to better classification performance for a specific type of interaction. Each device has been equipped with an accelerometer (ACC), a magnetometer (MAG), a gyroscope (GYRO), and a microphone (MIC). Generally, we observe that the features extracted from GYRO and ACC exhibit high distinctiveness for most of the interaction types. For ON-OBJECT, the most distinctive features originate from GYRO whereas for OFF-OBJECT, ACC appears to supply the most distinctive features. We observe that, in many cases, the inputs from co-located objects generate higher RMI scores. On the other hand, the features extracted from MIC appear to have relatively low distinctiveness in comparison to other attributes for the majority of interactions.

Despite its generally low distinctiveness for most interactions, MIC achieves higher RMI values for interactions with the pull-out drawer and is the second most distinctive sensor for the coffee machine when we consider features extracted only from its on-device sensors. This can be explained as the drawer's contents make sounds continuously, changing based on how far extended the drawer is, whereas for most other events the main sounds were caused by the closing of doors—with little difference between users. Pressing the buttons of the coffee machine on the other hand makes faint sounds which differ between users with regards to the timing of the button presses.

GYRO shows particularly high distinctiveness for most interactions for ON-OBJECT, with the exceptions of the narrow cabinet and the pull-out drawer. The cabinet used in the experiment has a very stiff door that leads to abrupt openings with little variation between users. While this reduces the effectiveness of the recognition of users by sensors directly placed on the cabinet, such abrupt openings allow co-located sensors to capture stronger vibrations, hence, provide more accurate distinction. The lower RMI values for GYRO for the pull-out drawer can be explained by a lack of rotational movement. Instead, the most distinctive movement characteristics are the sounds and the acceleration which is why MIC and ACC are the most distinctive sensor types for this interaction.

ACC appears to provide the most distinctive features captured by co-located sensors. Interestingly, the vibration signals picked up by the co-located sensors exhibit the highest feature distinctiveness during interactions with the coffee maker. Overall, we notice that OFF-OBJECT features provide better distinctiveness than the features gathered only by ON-OBJECT sensors. This suggests that the system can accurately authenticate users by their interactions with objects that do not have sensors directly placed on them.

6.2 Authentication Performance

In our experiment, we focus on analyzing the system performance against three types of attacks. The first part of the dataset contains the samples from the victim as well as zero-effort attack samples from each of the remaining 12 participants. This dataset is split using 10-fold cross-validation. Each test fold is used to evaluate a group of zero-effort attacks since it contains the samples of attackers' regular interactions with objects. The remaining attack samples are supplied to the zero-effort attack-trained classifier. To compare and evaluate the effectiveness of different types of attacks on the environment, we report False Reject Rates (FRRs) at different thresholds of

Table 1: Aggregated maximum values of RMI in % for different configurations.

(a) On-object configuration, given different types of on-device sensors.

Object Type	ACC	MAG	GYRO	MIC
Right cupboard door	30.08	40.58	71.86	18.28
Wide cupboard	50.95	47.30	64.45	25.37
Left cupboard door	62.90	39.50	73.90	9.82
Narrow cabinet	30.39	33.28	19.41	15.78
Oven door	32.24	64.46	48.18	14.33
Coffee machine	34.07	40.64	60.48	41.67
Pull-out drawer	37.20	27.21	21.95	41.00
Microwave door	35.43	54.14	41.12	14.14

(b) Off-object configuration, given different types of co-located sensors.

Object Type	ACC	MAG	GYRO	MIC
Right cupboard door	79.21	68.89	72.08	22.80
Wide cupboard	85.86	53.72	59.10	26.57
Left cupboard door	77.69	75.53	74.21	16.26
Narrow cabinet	76.51	73.43	61.28	23.31
Oven door	79.23	73.52	60.76	17.93
Coffee machine	98.19	69.44	90.41	42.96
Pull-out drawer	81.21	73.12	57.56	28.70
Microwave door	86.09	54.00	58.37	20.65

Table 2: False Reject Rates (FRRs) for interactions with different types of objects in respect to three kinds of attacks given different FAR thresholds. The On-object column presents FRRs for the model with features extracted only from on-device sensors. Off-object shows FRRs considering only features from co-located sensors, whereas Combined reveals FRRs for the model that uses the combined features from the co-located and on-device sensors. The results are averaged across all smart objects in our experiment.

FAR	**On-object FRR**			**Off-object FRR**			**Combined FRR**		
	Zero-effort	Video	In-person	Zero-effort	Video	In-person	Zero-effort	Video	In-person
10%	0.0875	0.3335	0.1875	0.0	0.05	0.1125	0.025	0.2125	0.1688
1%	0.2375	0.5909	0.4938	0.0063	0.0625	0.1563	0.025	0.2375	0.2625

False Acceptance Rates (FARs). The FAR metric allows us to determine how many attempts the attacker was successful in. On the other hand, FRR specifies how many legitimate samples from a victim have been misclassified as an attack. Note that rather than completely preventing the user from executing a transaction, this merely means that the user will have to approve the transaction explicitly through their phone.

First, we examine FRRs for individual smart objects that the user interacts with. Next, we inspect the performance of ensembles of base-classifiers that are responsible for interpreting different interactions with objects. Finally, we compare the performance of voting and stacking meta-classifiers by examining the receiver operating characteristic (ROC) curve for an ensemble of all available object interactions. In Table 2, we present FRRs at 1% and 10% FAR thresholds averaged across all objects for three types of attacks targeting a dedicated user. Figure 6 shows their averaged ROC curves. Table 3 presents FRRs for individual smart objects in respect to zero-effort attacks without a dedicated victim, i.e., the results are averaged across all users being considered a victim. For each attack, we calculate FRRs and FARs using different system configurations, including On-object, Off-object, and Combined. For Off-object, only the top performing features are selected.

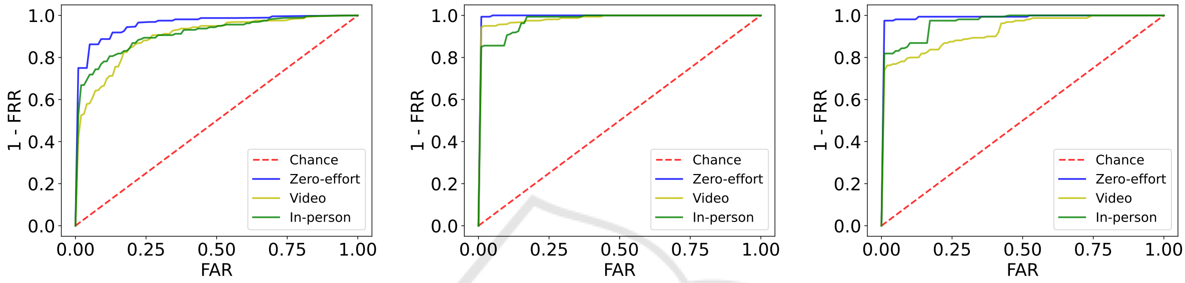
In the training phase, we only use samples collected during participants' regular interactions with the smart environment. This is because we consider an attacker who has access to the facilities—for example, a malicious co-worker whose typical interaction samples would be known by the system. A zero-effort attack, in which the attacker does not attempt to mimic the behavior of a legitimate user, is an indication of the baseline performance of the system. Other types of attacks involve attackers who either watched the video of the victim interacting with objects or observed the victim personally.

We observe that for authentication using Off-object sensors, we achieve an average false reject rate of less than 1% with a 1% false acceptance rate for zero-effort attacks. FRRs increase to 6% for video-based attacks and to 16% for in-person observation-based attacks, considering the same false acceptance rate. This means that even when defending against strong video-based or in-person mimicry attacks, the system does not require the user to explicitly approve transactions in more than 84% of cases, as the system can instead authenticate the user through their interactions with the smart environment.

For the FAR of 10%, the FRR for zero-effort attacks drops to less than 1%. Similarly, FRRs for video-based and in-person attacks decrease to 5% and 11% respectively. The On-object configuration exhibits the worst performance among all of the configuration types, resulting in false reject rates of 24% for the zero-effort attacks, 59% and 49% for the other types of attacks. The Combined configuration guarantees better performance than On-object, however, it exhibits worse performance than Off-object due to the inclusion of features extracted from on-device sensors. It is noteworthy that the microwave door and the narrow cabinet classifiers perform signif-

Table 3: FRRs at two distinctive FAR thresholds for interactions with different types of objects in respect to zero-effort attacks given ON-OBJECT and OFF-OBJECT configurations. These configurations are compared to emphasize the improvement offered by considering co-located sensors. Presented results are averaged across all users being considered a victim.

Object Type	***FAR* = 10%**		***FAR* = 1%**	
	ON-OBJECT FRR	OFF-OBJECT FRR	ON-OBJECT FRR	OFF-OBJECT FRR
Right cupboard door	0.0526	0.0039	0.1401	0.0154
Wide cupboard	0.0577	0.000	0.2231	0.0077
Left cupboard door	0.0369	0.0039	0.1077	0.0039
Narrow cabinet	0.1141	0.0	0.2577	0.0039
Oven door	0.0305	0.0	0.1020	0.0
Coffee machine	0.0154	0.0	0.0731	0.0
Pull-out drawer	0.0385	0.0	0.1180	0.0
Microwave door	0.0987	0.0115	0.2962	0.0192



(a) ON-OBJECT. (b) OFF-OBJECT. (c) COMBINED.

Figure 6: The plots above show the ROC curves for three system configurations respectively based on average FARs from single interaction types. Each curve represents a different group of attacks, i.e., zero-effort (blue), in-person (green), and video-based (yellow) attacks.

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icantly worse than others, which impacts the average scores. Since this effect is universal across users, this suggests that poorly-performing objects should be excluded by the meta-classifier.

Table 3 compares the performance of ON-OBJECT and OFF-OBJECT configurations across all smart objects. The narrow cabinet and the microwave door exhibit the worst FRRs in the ON-OBJECT configuration, resulting in false reject rates of 26% and 30% given a 1% false acceptance rate for zero-effort attacks. The FRRs drop to 0.4% and 1% when the model includes features extracted from co-located sensors. Since the OFF-OBJECT configuration exhibits the best performance, we focus on it for the remainder of this section.

The attackers from the video group could watch the video of the victim performing interactions with objects as often as desired for 24 hours. On the other hand, the attackers who observed the victim in person could follow them closely and look at the exact body and hand movements. To understand this phenomenon, we asked the participants to describe their strategies. The participants from the video-based attack group watched the video three times on average before attempting to mimic the victim. When viewing the video, participants report that they paid attention to the strength with which the victim interacted with the objects, the use of the hands (left or right), the speed of the interaction, and the body position. The participants in the second group, on the other hand, focused mainly on the pace, strength, and rhythm of the interaction. All attackers focused their strategy on mimicking the power and speed with which the victim interacted with objects. Additionally, most of them attempted to spend a similar amount of time per interaction as the victim did. One of the attackers even counted the seconds spent on each interaction.

Considering multiple interactions with various objects can further improve the system's performance. Figure 7 shows averaged FRRs at two FAR thresholds of 10% and 1% for different ensembles of objects for the voting and stacking meta-classifiers given the OFF-OBJECT configuration. We focus on the OFF-OBJECT configuration here, as it exhibits the best performance out of the three considered configurations, and thus best demonstrates the potential performance gains that can be achieved. This could be further improved by adjusting the weights, i.e., assigning smaller ones to interactions that exhibit worse performance. Generally, allowing the system to consider more interactions before authenticating the user results in better performance. Overall, the voting

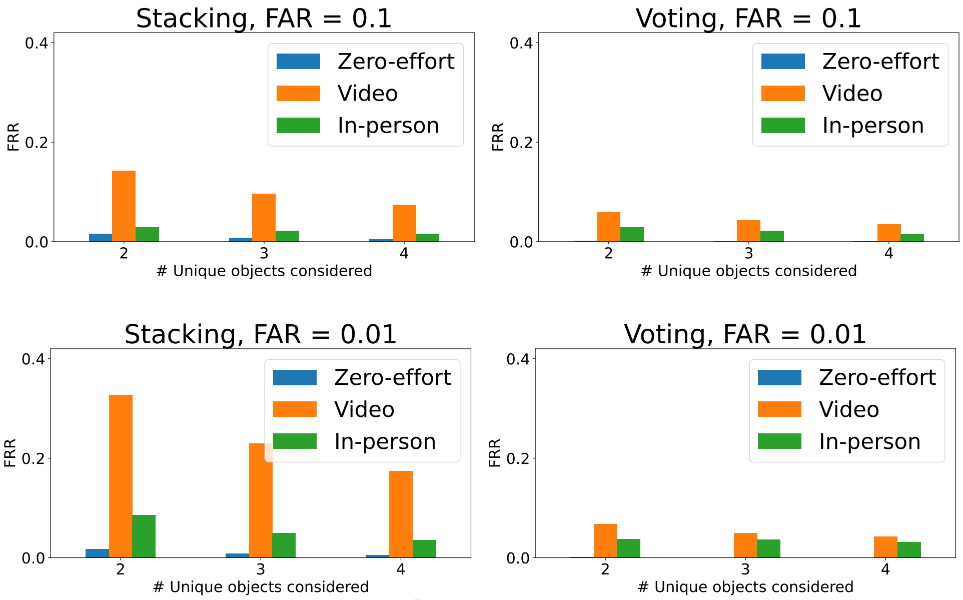

Figure 7: Averaged False Reject Rates (FRRs) at different False Acceptance Rates (FARs) thresholds calculated based on the performance of different ensembles of unique objects for two meta-classifiers and the OFF-OBJECT configuration. Each such ensemble is trained and tested separately, then the scores are averaged across the ensembles of the same type (e.g., pairs, triples of unique objects).

method outperforms the stacking meta-classifier in our scenario. This method is also computationally less complex since it does not involve training another classifier with the predictions of the base-classifiers. The voting meta-classifier achieves a false reject rate of less than 1% with a FAR of 1% whereas the stacking classifier obtains a FRR of 2% for the zero-effort attacks. The video-based attacks for the stacking classifier achieve a FRR of 33% when considering the ensemble of two unique objects given a FAR of 1%. On the other hand, the voting classifier obtains 7% FRR given the same FAR threshold. This means that for the voting classifier, the system can spare the user an explicit phone-based authentication in 93% of cases. We included only four smart objects in this analysis but considering more unique smart objects results in further improvements of the system performance.

7 LIMITATIONS

In this section, we discuss *BeeHIVE*'s limitations:

No Concurrent Device Use. In our experiment, we limit interactions with any device to a single user at a time. In the experiments, this was necessary to obtain accurate identity labels to establish the distinctiveness of device interactions. This limitation may lead to two potential problems in practice. If two users are interacting with different devices in the same room simultaneously or in short sequence, this may lead to decisions made using multiple device interactions to be wrong. This can be avoided by only using interactions with the target device (the device requiring authentication) to make the decision.

Limited Number of Users and Interactions. Due to time considerations and the unique requirements of the ongoing Covid-19 pandemic, we could only capture device interactions in a single session. This limits our analysis for different levels of FAR and FRR, as the total number of samples and attacker/victim pairs are too low to make a statistically robust analysis of extremely low FAR levels. Given the promising results shown by our current analysis, we plan to collect an additional large-scale dataset in the future.

Contiguous User Sessions. In our experiment, sessions for different users were conducted one after the other. In theory, it would be possible for environmental effects to be present during one user's session but not for others, thereby leading to classifiers learning these effects as a proxy for user identity. For example, a sound pressure sensor may pick up increased ambient noise during a user's session. However, the fairly strong increase in FAR caused by imitation attacks (video and in-person) suggests that the classifiers capture (somewhat imitable) true user behavior as it is unlikely users would attempt to match the original environmental conditions during their attack.

8 CONCLUSION

In this paper, we have introduced a system to authenticate users in smart environments based on naturally occurring interactions with objects around them. Notably, our system does not require any sensors on the object itself but makes use of sensors placed arbitrarily in the room. We have conducted an experiment in real-world settings with a total of 13 participants, which shows that using these kinds of smart object interactions for authentication is feasible. This is a crucial finding because there is a need for stronger authorization controls in such environments, but many smart devices offer only limited interfaces to implement security features. Therefore, current systems often rely on cumbersome app-based authentication methods that require the user to always have their phone at hand. Our system can complement such phone-based authentication methods and reduce how often a user has to explicitly approve a transaction in the smart home companion app.

We show that our system demonstrates good authentication performance against zero-effort attacks, with less than 1% of transactions requiring external approval at a FAR of 1% when considering a single object interaction. When attackers attempting to imitate the victim's behavior after observing them in-person or through video footage are considered, the user has to approve more transactions explicitly to maintain a 1% FAR. However, the system can still authenticate more than 84% of transactions unobtrusively when considering in-person attackers, rising to 94% of transactions for video-based attacks. We also show that the system's confidence in the authentication decision can be significantly improved if more than one object interaction is considered.

These promising results and the potential for easy deployment make this behavioral biometric system a good candidate to improve the security of smart environments in a seamless and unobtrusive manner. We make our entire dataset and the code needed to reproduce our results available online to allow researchers to build on our work.

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A CLASSIFIER HYPER PARAMETERS

Table 4: Search space for classifier hyperparameters. As each base classifier choses their own parameters, the optimal values given here are the most commonly chosen ones.

(a) Random Forest (RF).

Parameter	Search space	Optimal value
Number of estimators	10, 50, 100, 200	100
Tree depth	2, 4, 5, 6, 7, 8	7
Number of features	$\sqrt{N_F}$, $\log N_F$	$\sqrt{N_F}$

(b) Support-vector Machine (SVM).

Parameter	Search space	Optimal value
C	0.1, 1, 10, 100	0.1
γ	1., 0.1, 0.01, 0.001	0.01
Kernel function	linear, polynomial, rbf, sigmoid	rbf

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