Fingerprinting Robot Movements via Acoustic Side Channel

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ABSTRACT
In this paper, we present an acoustic side channel attack which makes use of smartphone microphones recording a robot in operation to exploit acoustic properties of the sound to fingerprint a robot’s movements. In this work we consider the possibility of an insider adversary who is within physical proximity of a robotic system (such as a technician or robot operator), equipped with only their smartphone microphone. Through the acoustic side-channel, we demonstrate that it is indeed possible to fingerprint not only individual robot movements within 3D space, but also patterns of movements which could lead to inferring the purpose of the movements (i.e. surgical procedures which a surgical robot is undertaking) and hence, resulting in potential privacy violations. Upon evaluation, we find that individual robot movements can be fingerprinted with around 75% accuracy, decreasing slightly with more fine-grained movement meta-data such as distance and speed. Furthermore, workflows could be reconstructed with around 62% accuracy as a whole, with more complex movements such as pick-and-place or packing reconstructed with near perfect accuracy. As well as this, in some environments such as surgical settings, audio may be recorded and transmitted over VoIP, such as for education/teaching purposes or in remote telemedicine. The question here is, can the same attack be successful even when VoIP communication is employed, and how does packet loss impact the captured audio and the success of the attack? Using the same characteristics of acoustic sound for plain audio captured by the smartphone, the attack was 90% accurate in fingerprinting VoIP samples on average across baseline movements, which is around 15% higher than the baseline without the VoIP codec employed. This is an interesting result as it opens up new research questions regarding anonymous communications to protect robotic systems from acoustic side channel attacks via VoIP communication networks.

CCS CONCEPTS
• Security and privacy → Systems security; Side-channel analysis and countermeasures.

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1 INTRODUCTION
The prominence of teleoperated robotic systems has seen a recent rise in a variety of application areas, such as industrial [55] and surgical environments [2, 65], with promises of higher levels of accuracy and precision. Given that many of these systems are becoming increasingly connected, they are vulnerable to an expanded threat landscape in the cyber domain. Attacks from this angle are primarily active attacks such as tampering with the integrity of messages in-flight or hijacking the robot controller directly [13]. However, little attention has been paid to the capabilities of a passive attacker and the damage potential of stealthier attacks. Specifically, passive attacks such side channel attacks which exploit information leakages without the need to change the normal behaviour of the system, can result in huge losses that stem from the compromise of operational confidentiality. Side channel attacks in the cyber domain have the potential to compromise the operational confidentiality of organisations that own such systems [62], yet those targeting robots in the physical domain are still to be explored.

In this paper, we aim to investigate whether an adversary can exploit information leakages from the acoustic side channel, by capturing audible emanations from a robotic system during normal operations, to mount an attack that targets operational confidentiality. In this context, we look at two possible threats posed by an insider attacker. First, a malicious robot operator or technician on the ground could use a recording device, such as a smartphone, near the robot to record entire workflows or individual movements. By fingerprinting this leaked information, they could sell this on to competing organisations for a malicious advantage. While it can be argued that an attacker may not be able to get close enough to the robot to place the recording device, many robotic systems now employ sensors to aid safety mechanisms to prevent harm to nearby humans or environmental changes. This can allow the attacker windows of opportunity to place the recording device near the robot or be near enough to capture meaningful acoustic emanations. A second possible threat comes from a telemonitoring perspective. While telemonitoring is less common in industrial settings, in surgical settings the use of medical recording devices, such as medical data recorders or intraoperative video recorders, are used for post-surgical review or teaching (alongside patient consent) to learn from suboptimal scenarios and improve performance [3, 61, 69].
While privacy laws and medicolegal requirements govern the use of such devices, data from them is not typically required as evidence in court so long as patient confidentiality is maintained [18]. However, acoustic emanations captured by such recordings could reveal the operations the robot is carrying out, and ultimately piece together surgical procedures. In combination with other metadata, such as patient admission and exit times, this could compromise patient confidentiality.

In this attack, we recorded the acoustic emanations, through a smartphone recorder, for individual robot movements, as well as recording entire workflows corresponding to typical warehousing operations such as picking and placing objects from one place to another. Using the collected data, we extract a set of acoustic characteristics which are used as input to an artificial neural network (ANN). We found that baseline movements (of minimum speed and distance) can be fingerprinted with at least ~75% accuracy as a baseline. The speed and distance of movements are not as successfully fingerprinted in this attack, compared to the radio frequency side channel. Entire warehousing workflows with ~64% accuracy. Ultimately, it is clear that a passive insider adversary has the potential not only to reveal what a robot is doing but take the resulting liabilities of such an attack to an extreme that impacts even the organisations that employ them. As well as this, in certain robotics environments, such as in surgical settings, procedures may be streamed and/or recorded for viewing, education or research [28, 38, 47]. Therefore, it is important to question how VoIP impacts the audio samples for movements and workflows and, ultimately, the success of the attack. Using the Opus codec – a common choice for most modern VoIP applications – the attack was 90% accurate for computing movement fingerprints for baseline speed and distance, which is nearly 15% more accurate than the baseline without the Opus codec employed, presenting new research questions regarding side channel attacks via VoIP communication networks which target robotic systems.

The remainder of this paper is as follows. In Section 2 we provide background on teleoperated robots and acoustic emanations, to which we then describe the threat model. We then outline the attack and our findings in Section 3, and provide an in-depth discussion in Section 5. In Section 6 we discuss related work and conclude in Section 7.

2 BACKGROUND

2.1 Teleoperated Robots

The use of robotics has seen an increase in installations in a variety of application areas [59] and play pivotal roles bringing benefits to quality of service, efficiency and precision, among others. Among them, teleoperated robots are most prominent in many industrial [6, 8, 11, 24, 41] and surgical [27, 64, 65] environments, and share a common system architecture. This type of system makes use of a human operator (i.e. a specially-trained surgeon) who operates the controller (i.e. surgeon’s console or teach pendant) which translates human movements or inputs into those which the robot can interpret. These input (console and other sources of information) and output (actuators) devices are linked together via an electronic control system (ECS) and typically connected to the organisation’s network in which the robot operates. An overview of a typical teleoperated robot architecture can be seen in Figure 1.

![Figure 1: Teleoperated Robot Architecture](image)

2.2 Acoustic Characteristics

While the robot moves, its electromechanical components will emit (audible) sound, which when captured could be used to mount an information leakage attack. The first step to determining an appropriate attack strategy is to understand the different characteristics of acoustic emanations, and what may be most useful from an attack perspective.

2.2.1 Root Mean Square Energy. Root Mean Square (RMS) energy [9] is a measure of the amplitude based on all samples in a frame of audio, and can be thought of as an indicator of loudness of the audio signal [51]. This may be useful in the context of this attack given that combinations of movements (i.e. simultaneous movements along 2 or more axes) may emanate a louder sound given the use of more stepper motors, for example. As well as this, as the robot axes pass the microphone, the sound may be louder and thus this feature may help provide further information to the discrimination between movements in different positions.

2.2.2 Zero-Crossing Rate. Zero-Crossing Rate (ZCR) is a measure of the number of times a signal crosses the horizontal time axis and can help identify pitch variations in monophonic tones (sound emitted from one location) [51]. Given the robot is stationary in this case, the ZCR may be a useful feature candidate.

2.2.3 Spectral Centroid. The spectral centroid provides information corresponding to frequency bands contain most of the energy, wherein lower centroid (energy) values is likened to duller sounds and higher centroid values for brighter sounds [40]. In a robotic system, smaller movement distances and speeds will naturally require less energy and appear more dull sounding to the human ear, whereas faster and longer movements have better tonality, and may ultimately provide useful for distinguishing between different movements of the same source.

2.2.4 Spectral Bandwidth. Spectral bandwidth is defined as the full width of band of light (wavelength interval) at half the peak
As well as this, it is also possible than an insider attacker is able to make up the MFC. The MFC equally distributes frequency to the attacker remotely or be retrieved at a later time. In either covertly plant a smartphone, which they may have on them and use covertly [53].

2.2.5 Spectral Rolloff. Spectral rolloff is the fraction of frequency bins under a cutoff point where the total energy of the spectrum is contained, and can help distinguish between noisy sounds and more harmonic sounds (below roll-off point) [36]. This feature may provide useful to this attack as it can roll off frequencies that may fall outside of the useful range of frequencies where the energy of the acoustic energy of movements is contained.

2.2.6 Spectral Contrast. Spectral contrast is the measure of energy of frequencies in windows of time [31] and can help identify strong spectral peaks to reflect the distribution between harmonic and non-harmonic components of the acoustic emanations. As a robot moves, the frequency contents may have energy that changes with time and capturing the spectral contrast can help measure this energy variation.

2.2.7 Chroma Feature. Chroma feature, sometimes referred to as a chromagram, profiles a sound into 12 pitch class profiles [48]. In music analysis, the attempt is to capture the harmonic and melodic characteristics of a song where pitches can be categorised to one of the scales in the equally-tempered set of the notes \{C, C#, D, D#, E, F, F#, G, G#, A, A#, B\} [16, 52]. While recorded robot movements are not akin to songs that are analysed in this fashion, the pitch of sound may correlate with the speed and distance of movement and may provide useful as a mid-level feature for fingerprinting movements.

2.2.8 Mel-Cepstrum Frequency Coefficients. The Mel scale is a scale of pitches that is felt to be equal in distance from one another. For example, in audible acoustics listened by a human, differences in frequency content can be observed if the source of acoustic emanations are in the same distance and atmosphere [26, 44]. The short-term power spectrum of acoustic emanations can be represented by the Mel frequency cepstral (MFC) and a combination of coefficients (MFCCs) make up the MFC. The MFC equally distributes frequency bands to approximate human auditory response. If variations in robot movements can be inferred from audible sound, then looking at the mel frequency coefficients (the list of amplitudes of the spectrum in the mel scale) will provide useful information to the attack.

2.3 Threat Model

Many previous attacks focus on an active attacker, which can involve the tampering of messages [13] or replaying attacks between the robot or controller [45]. In this work, the primary attacker is a passive insider, such as a malicious technician or operator. Being an insider close to the robot would allow them to record the acoustic emanations during the robot’s normal operations using a smartphone, which they may have on them and use covertly [53]. As well as this, it is also possible than an insider attacker is able to covertly plant a microphone which could transmit recorded audio to the attacker remotely or be retrieved at a later time. In either case, if an attacker is able to mount an information leakage attack to fingerprint robot movement patterns from acoustic emanations, this could lead to the revelation of daily workflows (i.e. in a warehouse) and ultimately compromise the operational confidentiality of the organisation. For example, this information could be given to competitors to gain an advantage or use it maliciously.

A second possible threat comes from a telemonitoring perspective. While telemonitoring is less common in industrial settings, in surgical settings the use of medical recording devices, such as medical data recorders or intraoperative video recorders, are used for post-surgical review or teaching (alongside patient consent) to learn from suboptimal scenarios and improve performance [3, 61, 69]. While privacy laws and medicolegal requirements govern the use of such devices, data from them is not typically required as evidence in court so long as patient confidentiality is maintained [18]. However, acoustic emanations captured by such recordings could reveal the operations the robot is carrying out, and ultimately piece together surgical procedures. In combination with other metadata, such as patient admission and exit times, this could compromise patient confidentiality.

Ultimately, reviewing the nature of acoustic emanations in robotic systems, as well as the proposed threat model, the aim is to investigate whether an adversary will be able to record the acoustic emanations from a robot during its normal operation, and make use of distinct features present across the recorded audio to fingerprint robot movements and workflows. Several hypothetical factors will come into play which could influence the potential success of this attack. First, the type of operations being carried out by the robot can vary in terms of speed and distance of movement, and so the attack should be robust enough to fingerprint between these parameters. Second, the distance at which the microphone is situated away from the robot, naturally due to the Doppler effect [21] wherein sounds soften with distance, will also have an impact on the success of the attack and should be investigated. Finally, given that in some cases VoIP technology will be employed, such as for recording purposes or to livestream medical procedures with surgical robots, the impact of VoIP on the attack should be evaluated.

2.4 Hypotheses and Goals

In this work we aim to investigate whether an adversary will be able to effectively record the acoustic emanations from a robot during its normal operation, and make use of distinct features present across the recorded audio to fingerprint robot movements and workflows. We hypothesise that several factors will come into play which could influence the potential success of this attack. First, the type of operations being carried out by the robot can vary in terms of speed and distance of movement, and so the attack should be robust enough to fingerprint between these parameters. Second, we also hypothesise that the distance at which the microphone is situated away from the robot, naturally due to the Doppler effect [21] wherein sounds soften with distance, will also have an impact on the success of the attack and should be investigated. Ultimately, the following research questions are proposed:

(R1) Can an attacker fingerprint individual robot movements on each axes, as well as permutations of them?
How is movement fingerprinting affected by:
(i) The speed and distance of movements?
(ii) The distance the recording device (i.e. smartphone) is away from the robot?

Can entire robot workflows be reconstructed from acoustic emanations?

How do VoIP codecs influence the success of the attack?

3 ATTACK METHODOLOGY

In this paper, we investigate an acoustic side-channel attack which exploits audio emanations from a robot during its operation. Specifically, the aim of this attack is to fingerprint a robot’s movements from acoustic characteristics alone, recorded by smartphone devices in a passive manner. For subsequent discussion, we aim to answer the following questions:

Can an attacker fingerprint individual robot movements on each axes, as well as permutations of them?

How is movement fingerprinting affected by:
(i) The speed and distance of movements?
(ii) The distance the smartphone or microphone is away from the robot?

Can an attacker recover information about the objects a robot is handling, such as its weight?

Figure 2: Robot Environment for Acoustic Side Channel

3.1 Robot Environment

The context of this study surrounds modern teleoperated surgical robots, whose typical architecture can be viewed (at a high level) as a pairing between the robotic system itself and its controller (surgeon’s console). For this work, we use uFactory’s uARM Swift Pro which runs on an Arduino Mega 2560 with MicroPython installed. The controller is emulated on a Windows 10 laptop which uses the uARM Python (3.8.X) SDK to enable controller instructions to be written in Python which are then translated into Gcode that is understood by the robot. An overview of the robot environment used in this study is depicted in Figure 2. For capturing the acoustic emanations during each robot operation, we position the robot in the center of a table with the smartphone/microphone placed in several distances away (30cm to 1m) from the robot as shown in Figure 2.

Figure 3: Depiction of Common Warehousing Workflows

Our dataset contains common warehousing workflows such as pushing, pulling, packing and moving objects.

Figure 3: Depiction of Common Warehousing Workflows

Our dataset contains common warehousing workflows such as pushing, pulling, packing and moving objects.

3.2 Experiment Parameters

With the robot setup for evaluating our acoustic side-channel attack for fingerprinting the robot’s movements, we now outline the

Figure 3: Depiction of Common Warehousing Workflows

Our dataset contains common warehousing workflows such as pushing, pulling, packing and moving objects.

parameters of our study. Specifically, we will discuss the speed and distance of the movement operation being carried out, the type of smartphone/microphone, the distance the smartphone microphone is away from the robot and finally, Speed and Distance. In addition to capturing the acoustic emanations which arise during operation along the X, Y and Z axes, and combined movement operations, it is important to evaluate more fine-grained movements. To this, we programmed robot movements with varying distances (in millimetres) as well as varying speeds of movement (mm/s). This is because in realistic cases, a surgical robot for example would not move in each direction with constant distance and speed. Therefore, it is vital to understand whether an adversary can also fingerprint meta-information as well as just the movements themselves.

Microphone Distance. In terms of recording the acoustic emanations during robot operation, it is important to evaluate the impact of distance the microphone is away from the robot. In a real situation, it is highly unlikely that an adversary would be very close to or in front of the robot, especially in cases like surgical robots where it could not only be dangerous to stand too close but being close enough may trigger potential safety features implemented to prevent injury. For this study, given the size of our uARM robot (150mm x 140mm x 281mm) and the volume of sound which is given off during its operation, we cannot investigate large distances as would be granted with a large surgical robot, for example. However, given this limitation, we recorded sounds at distances ranging from 30cm to 1m.

VoIP. The final parameter for this study is to evaluate the impact VoIP has on the success of the attack. For this study, the codec employed by the majority of VoIP applications is Opus [67, 68]. The first step is to observe how the codec performs, but also how packet loss will also affect audio quality and the success of the attack.

3.3 Movement Dataset

After determining the appropriate acoustic features to extract from the captured sounds, the next step was to create the dataset. In this
dataset, there are 2 subsets. Within both subsets, there are samples pertaining to both individual and permutations of movements with varying speeds and distances of movement, the microphone distance, and robotic warehousing workflows (Figure 3). These workflows include those such as pick-and-place, push and pull operations, which were replicated from those found in existing industrial robot datasets such as the Forward Dynamics Dataset Using KUKA LWR and Baxter [54] for pick and place and the Inverse Dynamics Dataset Using KUKA [60] for push/pull. For these workflows, movements were slightly perturbated to account for a small degree of entropy that may be present in real-world operations (i.e. those that may arise due to drift in equipment calibration or wear-and-tear). In contrast to the first subset, the second subset contains the same samples but are passed through the Opus codec to evaluate the impact of VoIP on recorded audio in this attack. Specifically, while all samples are passed through the Opus codec, they are further split by packet loss. Packet loss has been shown to negatively impact call quality in VoIP communications [39, 50], as they induce impact in the form of dropped calls or parts of speech, slow rate of speech (latency) or noise/interference. Because of this, these further subsets are divided by packet loss values of 1%, 5%, 10%, 25% and 50%. As a whole, the first subset contains 27.2K samples for individual movements and 658 samples for warehousing workflows, with each using 20% of the total samples for validation and another 20% for testing. The second contains the same amount of samples for each of the packet losses evaluated.

**Dataset Pre-Processing.** The features in the dataset, as listed above, are computed using the librosa [46] Python library. For each feature, the mean value of each feature across each signal sample is taken and computed from a Short-Time Fourier Transform (STFT) with a Hann window and FFT length of 8192. For the MFCCs, 14 coefficients were used. Typically, 8–13 are used with the zeroth excluded given it only represents the average log-energy of the input signal [58]. However, given this is a new problem to be explored, this is also kept to later examine its importance for fingerprinting.

### 3.4 Neural Network

Before an evaluation can take place, an important step is constructing an appropriate neural network architecture for fingerprinting movements and ensuring a successful attack. To create the neural network, a sequential model was used where neurons are grouped in a linear fashion. This was created using the Keras API [17]. The parameters and structure for the layers in the neural network were evaluated on the dataset using a cross-validated grid search to find the most optimal number of neurons, layers, activation function and dropouts if necessary. The input for the maximum number of neurons to be tested was calculated using the formula proposed by Demuth et al. [19] with an alpha branching factor of 2. Using the grid search with 3 cross validations, the most optimal neural network architecture for this feature set consists of 5 layers. First, the input layer containing 21 neurons for each of the input features. Next, there are 4 hidden layers. The first is a Dense layer with 290 neurons and uses the ReLU activation function [23]. The next hidden layer is a Dropout layer which is used to randomly set input units to 0 at a rate of 0.05 at each step during training to prevent overfitting. The next layer is another Dense layer of 350 neurons with ReLU activation, followed by another Dropout with a rate of 0.05 to prevent overfitting. Finally, the last layer is a Dense output layer of 7 neurons, one for each of the movement classes, and uses the SoftMax activation function [22] to have the output in the range of [0, 1] for use as predicted probabilities. Sparse categorical cross-entropy is used as labels are integers and not one-hot encoded, for which categorical cross-entropy would be used [71]. The optimiser used is Adam with a learning rate of 0.001. This learning rate was chosen as others, such as those with higher learning rates, resulted in lowered accuracy scores. The model was fitted with a batch size of 32 and was run for 1000 epochs.

**Choice of Activation and Optimisation Functions.** The ReLU activation function was chosen over other activation functions, as the reduced likelihood of vanishing gradient allows for a constant gradient resulting in faster learning. Further, the sparsity of representations are shown to be more beneficial than dense representations, as seen in other activations such as sigmoids [1, 37, 42]. The softmax activation function, combined with categorical cross-entropy [71] for the loss function, was chosen due to the simple fact that this is a multi-class classification problem. Simply, a sample can belong to one of the 7 classes, with each class corresponding to one of the robot movements. As well as this, the Adam optimiser was an ideal candidate. It is an extension to the Stochastic Gradient Descent (SGD) method, based on adaptive estimation of first- and second-order moments [34]. Specifically, it allows for the updating of network weights iteratively based on the training data, and fits best with the weighted sample sets in opposition to other tried methods such as standard SGD, RMSProp and SGD + Nesterov Momentum.

### 4 EVALUATION

After setting up the robot environment and capturing the acoustic emanations during various stages of operations, the next step is to evaluate the success of the attack. As per the research questions listed above, the evaluation of this attack and related results will be set out in that order.

#### 4.1 Individual Movement Fingerprints

The first research question (R1) aims to investigate whether an attacker can infer individual movements (on each axis) and permutations of these movements from the recorded audio. To compare this against other parameters, this experiment is considered as a baseline where the speed and distance of movement are the lowest possible values (1mm and 12.5mm/s respectively), and no VoIP codec used. As seen in Table 1, an average accuracy of around 75% can be observed across all movements, with the YZ movement having the highest precision among the movements. In comparison with the RF side channel, there is a clear drop in accuracy of around 20% but the acoustic side channel outperforms traffic analysis by around 10%. Interestingly, Y-involved movements are better recovered than other movements overall, which was not the case in the RF side channel (albeit a higher accuracy). This may be due to the Y-axis moving across the microphone range. Looking at the Z-involved movements, these are among the lowest. This may be due to the Z axis involving a vertical movement only and not moving nearer the microphone for better recording.
4.2 Impact of Movement Distance

For the next research question ($R_2$), the evaluation will look into how the distance and speed ($R_2(i,j)$) of robot movements, and the distance of the recording device ($R_2(j,i)$), impact the success of fingerprinting movements from the acoustic side channel. First, as a robot moves, there is likely to be more sound that can be recovered as the distance of movement increases. As seen in Table 2, an increase by a single distance unit increases the model accuracy by 1%, improving Y-involved movement precision by around 10%. Furthermore, the Z movement also gains a slight increase in precision. Unfortunately, this results in lowered accuracy for the other movements. This increase in distance results in the sound of movement being held for longer and may either provide useful for distinguishing variance between movements or even reduce this variance. To explore this, larger distances of movements are explored. At 5mm, there is a drop in accuracy of around 4%, with X-involved movements having much higher accuracy. At 10mm, the accuracy of the model overall decreases significantly to 57%, Y-involved movements which were previously described to have poorer accuracy for an attacker. Z-based movements show the lowest precision and recall for fingerprinting, perhaps due to vertical motion and no horizontal spread across the recording device.

| Movement | Precision | Recall |
|----------|-----------|--------|
| X        | 76%       | 81%    |
| Y        | 77%       | 78%    |
| Z        | 61%       | 71%    |
| XY       | 78%       | 80%    |
| XZ       | 68%       | 65%    |
| YZ       | 85%       | 78%    |
| XYZ      | 72%       | 67%    |

Accuracy 75%

Table 1: Baseline Classification Results

As a whole, the baseline accuracy is 75% which is fairly good inference accuracy for an attacker. Z-based movements show the lowest precision and recall for fingerprinting, perhaps due to vertical motion and no horizontal spread across the recording device.

4.3 Impact of Movement Speed

After looking at movement distance, the next parameter for robot movements is the speed at which the robot is moving along each of the axes ($R_2(i,j)$). As seen in Table 3, the speed parameter is less accurately fingerprinted by the attack compared to the distance parameter by at least 10% on average. Interestingly, a similar pattern is observed regarding X-involved movements, with accuracy increasing with speed, except from the XYZ movement. While there are slight drops in accuracy, the precision and recall across most movements remains similar as speed increases. This is interesting, as the initial hypothesis was that a higher speed would result in higher pitched acoustic emanations, however the results seem to contradict this. In any case, perhaps the perceptual characteristics for human audio, while a clear pitch change is present listening to the robot in the lab, the feature algorithms regarding pitch (i.e. chroma feature) may not pick up on this for robot sounds.

| Movement | Precision | Recall |
|----------|-----------|--------|
| X        | 69%       | 71%    |
| Y        | 88%       | 77%    |
| Z        | 65%       | 83%    |
| XY       | 68%       | 66%    |
| XZ       | 62%       | 57%    |
| YZ       | 94%       | 94%    |
| XYZ      | 69%       | 81%    |

Accuracy 76%

Table 2: Classification Results With Distance Parameter

At a slight increase in distance, the accuracy remains similar to the baseline, but further increases in distances lead to a reduction in fingerprinting accuracy. Notably, unlike the baseline, X-involved movement are better fingerprinted at distance.

4.4 Microphone Distance

While observing more fine-grained information leakage is useful to an attacker, one problem that may impact the success of the attack is the distance the recording device is away from the robot – in this case, the smartphone. Naturally, due to the Doppler effect, the intensity of sound (i.e. loudness) decreases over distances, and one would hypothesise that because of this the accuracy may be significantly impacted as the distance of recording increases. In this experiment, two other microphone distances (50cm and 100cm) are also tested in addition to the baseline recorded at 30cm. While these are not large recording distances, given the small scale of the robot used for the evaluation of the attack, these are relatively suitable candidates to be tested. As seen in Table 4, as the distance the microphone is away the robot is increased, the accuracy of the attack compared to the baseline decreases by around 10% at each recording distance step. Notably, this is much more significant for Z-based movements which were previously described to have poorer fingerprinting accuracy due to the limited range of motion that
workflows can be reconstructed through the acoustic side channel. As the microphone distance increases away from the robot being recorded, the next step in the evaluation looks at whether entire warehousing vertically. In this case, a point a future work may be to evaluate from the microphone (i.e. pull is a reverse of push) provides at least it can be hypothesised that only the direction of movement away the case of push and pull movements, they are highly similar and of movements and thus the variance helps with fingerprinting. In realistic settings, packets may arrive late, be dropped or be corrupted, which may result in not only a lowered audio quality but in the worst case, dropped parts of the audio or the entire audio sample entirely. Given that in VoIP applications, a 1% packet loss is considered an acceptable rate for VoIP to minimise impact on call quality [4, 30], however in the event of network failures or availability attacks this may be higher. For completeness, 5 packet losses of 1%, 5%, 10%, 25% and 50% are evaluated. Furthermore, as it was shown that constant bitrate quality does not perform as well as variable bitrate quality [57], samples are encoded and decoded with variable bitrate. This experiment used the same model as the previous experiments, but with a batch size of 256 and 100 epochs of training. As seen in Table 6, the results for the baseline speed and distance of movement (12.5mm/s and 1mm respectively) under various packet losses via the Opus codec can be seen. Interestingly, at low packet loss, the classification accuracy is around 90% and increases by around 15% compared to the baseline without VoIP employed. Further, X movements are more accurately fingerprinted across all packet losses compared to the baseline without VoIP. As the packet loss reaches more undesirable amounts of 25% and 50%, the accuracy slightly decreases but the accuracy still remains much higher than the baseline without VoIP. This may be due to the PLC algorithm switching between CELT or SILK mode and variable bit rate. Specifically, frames that are deemed important are re-encoded at a lower bitrate and allows for partial recovery for important lost packets. This may be targetting the movement audio within the sample thus leading to higher variance among classes.

### 4.5 Workflow Recovery

The next step in the evaluation looks at whether entire warehousing workflows can be reconstructed through the acoustic side channel attack. While a pattern matching approach can be successful using individual movement fingerprints, the ability to reconstruct entire workflows may be useful from an auditing perspective, for example, where offsets in normal movement signals can be flagged and investigated further. As seen in Table 5, the explored warehousing workflows can be recovered on average with around 62% accuracy. Notably, the pick-and-place and packing workflows are recovered with much higher success than the push and pull workflows. Simply, the former have much more variation in the pattern of movements and thus the variance helps with fingerprinting. In the case of push and pull movements, they are highly similar and it can be hypothesised that only the direction of movement away from the microphone (i.e. pull is a reverse of push) provides at least some degree of accuracy between the two.

### Table 4: Classification Results With Microphone Distance

| MD=30 | MD=50 | MD=100 |
|-------|-------|--------|
| X     | 76%   | 81%    | 68%    |
| Y     | 77%   | 78%    | 67%    |
| Z     | 61%   | 71%    | 48%    |
| XY    | 78%   | 86%    | 68%    |
| XZ    | 68%   | 65%    | 61%    |
| YZ    | 85%   | 78%    | 83%    |
| XYZ   | 72%   | 67%    | 52%    |

Accuracy 75% 65% 54%

### Table 5: Workflow Reconstruction Results

| Workflow     | Precision | Recall |
|--------------|-----------|--------|
| Push         | 37%       | 16%    |
| Pull         | 31%       | 59%    |
| Pick-and-Place | 100%     | 96%    |
| Packing      | 97%       | 100%   |

**Table:** Workflow Reconstruction Results

Common warehousing workflows can be reconstructed in their entirety are better recovered through the acoustic side channel if they are more complex and varied. Push and pull operations are less accurate due to the fact they are very similar movements.

### 4.6 Impact of VoIP

In certain robotics environments, such as in surgical settings, procedures may be streamed and/or recorded for viewing, education or research [28, 38, 47]. Therefore, it is important to question how VoIP impacts the audio samples for movements and workflows and, ultimately, the success of the attack. In many modern VoIP applications, the Opus codec is the preferred choice [67, 68] given its standardisation and rank of higher quality compared to other audio formats for a variety of bitrates. To explore this, the open-source nature of Opus allows for easy implementation to encode and decode the audio samples and, during decoding, investigate various packet losses. In VoIP applications, Packet Loss Concealment (PLC) is used as a decoder feature for receiving data from an unreliable source, which masks the effects of packet loss in VoIP communications.

5 DISCUSSION

The acoustic side channel attack we propose showcases the potential for successfully compromising the operational confidentiality of organisations in which robotic systems under attack are deployed. While many active attacks have shown to result in potentially devastating consequences, the capabilities of a passive insider attacker are truly underestimated. In this section, a discussion on the proposed attack is provided.

### 5.1 Influence of Noise

During the recording of acoustic samples for robot movements, there is likely some degree of background noise that should be accounted for. Given the recordings were made in a computer lab, background noise effects may include the likes of light chatter,
Interestingly, the precision and recall remains relatively similar across packet losses, with a slightly drop in accuracy for undesirable large packet losses. Notably, there is an increase in accuracy of around 15% compared to the baseline without the Opus codec employed keyboard tapping and rolling chairs, among others. While relatively good accuracy is observed even with the background noise, it is important to also look into techniques to eliminate such noise to determine whether this results in better fingerprinting accuracy.

In human audio, sound recordings contain the relative signal of the oscillations due to density and pressure of air in the ear. In digital audio, sound waves are encoded in digital form as numerical samples in a continuous sequence. The recordings taken in this attack are recorded at a sampling rate of 44.1KHz with 16-bit depth and thus there are 65,536 possible values the signal can take in the sequence.

As shown in Figure 4, the amplitude of the frequency content of the acoustic signal can be observed using the Fast Fourier Transform (FFT). In this attack, we make use of techniques originally applied to human acoustics, but given that the robot movements produce sound that is audible to the human ear as well. Looking at the frequency content, notable amplitude is not found past 1KHz, so this is zoomed in further to 250Hz. There is a notable spike around 60Hz, which is the frequency standard common to alternating current and is an effect known as electric hum due to electrical noise getting into an acoustic recording medium. The next largest peaks can be observed at around 150Hz and 200Hz which may correspond with robot movements. As a first step to noise reduction/filtering, one technique is amplitude filtering, where the amplitudes of FFT values to be filtered can be set to 0Hz, to which the original signal can be recreated using an inverse FFT. In this experiment, the electric hum, as well as frequencies outwidth the human hearing range of ~20Hz–20KHz are filtered by dropping the amplitude of these ranges. A depiction of the amplitude drop can be seen in Figure 5. Looking at Table 7, the accuracy of baseline movement fingerprints can be observed with amplitude filtering in place. While the accuracy overall decreases by 1% compared to the baseline without amplitude filtering, the precision for Y and XY movements increase. This may be due to unfortunate noise events present in these samples that the filter has rectified. However, there is still a reduction in overall accuracy, which may mean that electric hum and other peaks may not be the best indicators of noise to remove when recording a robotics system. In this case, as a point of future work other noise reduction techniques that have shown to be successful in other areas, such as stationary or non-stationary spectral gating [29, 49] which reduces noise in time-domain signals by estimating noise thresholds for the frequency bands in a signal to gate (mask) noise below the threshold, are worth exploring in the hope the attack accuracy may increase.

5.2 Other VoIP Codecs

Opus is the primary choice for many VoIP applications due to its royalty free and open source nature, alongside the benefits of higher quality and low-bandwidth streaming, in comparison with other codecs such as Speex [66] or SILK [70] (Opus’ predecessor). While it
While acoustic side channel attacks have not been explored for 3D printers [10] – some of which making use of smartphones to carry out the attack [12, 63] – and additive manufacturing systems [15]. However, many of these attacks solely focus on IP theft. The acoustic side channel attack presented in this work focus solely on the movement of the robot arm and the compromise of operational confidentiality, which when looking at the bigger picture is much more valuable to an attacker. Furthermore, the reconstruction of G-code is an unnecessary extra step as movements which correspond to these can be inferred from individual movement fingerprinting under the assumption the robot is operated by an Arduino. Furthermore, while the robot in this work is operated by an Arduino, the focus is on reconstructing movements from the acoustic emanations, irrespective of the microcontroller used and thus applies to robotic systems in general and not those restricted to being operated by an Arduino.

5.3 Defences

While the attack is successful, and even more so when the attack targets VoIP communications, a natural question pertains to countermeasures and defences against the acoustic side channel attack. In this work, acoustic emanations result in unintentional information leakages about robot behaviours and can ultimately lead to the compromise of operational confidentiality.

One defence that could be considered is to make use of vibration- or sound-reduction mechanisms to hinder the effect of the attack. As seen in Section 4.4, as the microphone distance increases the accuracy of fingerprinting also decreases. While this is due to the Doppler effect that is naturally at play with regard to sound intensity (i.e. loudness), a reduction in this from other means may result in the same outcome of reduced success of fingerprinting. Techniques in this space include the likes of using vibration isolation pads [20] or damping to reduce vibration [25, 32] for the robot as a whole. In the case of noise reduction for robot components such as stepper motors, potential defences include using a clean damper [43] or higher resolution stepper motors.

Another potential defence is to make use of a masking noise, to interfere with attack inference by distorting the signal related to information leakage in the acoustic side channel [5, 10, 33]. Adding a masking signal has shown success, but two challenges need to be addressed. First, the mask must be similar to the signal requiring masking to ensure difficult separation. Second, the masking noise should not cause any degrading effect on usability of the robotic system. For example, if the masking noise is to cover up other sound such as those used for emergencies or other operator feedback, then this will be much less than ideal and potentially lead to catastrophic liabilities.

6 RELATED WORK

While acoustic side channel attacks have not been explored for robotic systems, enhancing the novelty of this work, there has been previous research in the area of acoustic side channels. In a similar respect to robotics, the exploration of information leakage in the acoustic side channel has been explored for 3D printers [10] – some of which making use of smartphones to carry out the attack [12, 63] – and additive manufacturing systems [15]. However, many of these attacks solely focus on IP theft. The acoustic side channel attack presented in this work focus solely on the movement of the robot arm and the compromise of operational confidentiality, which when looking at the bigger picture is much more valuable to an attacker. Furthermore, the reconstruction of G-code is an unnecessary extra step as movements which correspond to these can be inferred from individual movement fingerprinting under the assumption the robot is operated by an Arduino. Furthermore, while the robot in this work is operated by an Arduino, the focus is on reconstructing movements from the acoustic emanations, irrespective of the microcontroller used and thus applies to robotic systems in general and not those restricted to being operated by an Arduino.

7 CONCLUSION

In conclusion, it is clear that even acoustic emanations provide a high level of accuracy for fingerprinting movements and showcases a highly important passive side channel attack in the physical domain, which can be carried out with a fairly cheap smartphone. While more fine-grained movements and entire workflows in warehousing settings can be inferred, our contributions demonstrate that the recent usage of VoIP technologies also leave potential for information leakage through these communication channels, with the result leaving movement fingerprints to be more accurately reconstructed. This is an interesting result as it opens up new research questions regarding anonymous communications to protect robotic systems from acoustic side channel attacks via VoIP communication networks.

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Table 7: Amplitude Filtering Classification Results

| Movement | Precision | Recall |
|----------|-----------|--------|
| X        | 72%       | 81%    |
| Y        | 75%       | 73%    |
| Z        | 68%       | 72%    |
| XY       | 86%       | 71%    |
| XZ       | 69%       | 68%    |
| YZ       | 76%       | 83%    |
| XYZ      | 72%       | 70%    |

Accuracy 74%

may be interesting to evaluate other codecs, Opus is the main choice for the majority of modern applications, such as Zoom, Teams and Discord [14, 56] and is taking over previously dominating codecs.
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