SATversary: Adversarial Attacks on Satellite Fingerprinting

Joshua Smailes University of Oxford joshua.smailes@cs.ox.ac.uk Sebastian Köhler University of Oxford sebastian.kohler@cs.ox.ac.uk

Martin Strohmeier armasuisse Science + Technology martin.strohmeier@armasuisse.ch Simon Birnbach University of Oxford simon.birnbach@cs.ox.ac.uk

Ivan Martinovic University of Oxford ivan.martinovic@cs.ox.ac.uk

Abstract—As satellite systems become increasingly vulnerable to physical layer attacks via Software Defined Radios, novel countermeasures are being developed to protect critical systems, particularly those lacking cryptographic protection, or those which cannot be upgraded to support modern cryptographic security. Among these is transmitter fingerprinting, which provides mechanisms by which communication can be authenticated by looking at characteristics of the radio transmitter, expressed as impairments on the signal.

Previous works show that fingerprinting can be used to classify satellite transmitters within a closed set, or authenticate them against SDR-equipped attackers under simple replay scenarios. In this paper we build upon this by looking at attacks directly targeting the fingerprinting system itself, with an attacker optimizing for maximum impact in jamming, spoofing, and dataset poisoning attacks, and demonstrate these attacks on the SATIQ system designed to authenticate Iridium transmitters. We show that an optimized jamming signal can cause a 50% error rate with attacker-to-victim ratios as low as -30 dB (far less power than traditional jamming techniques), and demonstrate successful identity forgery during spoofing attacks, with an attacker successfully removing their own transmitter's fingerprint from messages. We also present a data poisoning attack, enabling persistent message spoofing by altering the data used to authenticate incoming messages to include the fingerprint of the attacker's transmitter.

Finally, we show that our model trained to optimize spoofing attacks can also be used to detect spoofing and replay attacks, even when it has never seen the attacker's transmitter before. Furthermore, this technique works even when the training dataset includes only a single transmitter, enabling fingerprinting to be used to protect small constellations and even individual satellites, providing additional protection where it is needed the most.

1. Motivation

As the rise of off-the-shelf Software Defined Radio (SDR) hardware makes it easier for even hobbyist-level attackers to cause disruption to radio systems, legacy satel-

lite systems have been made particularly vulnerable due to their lack of cryptographic security. Physical layer fingerprinting has emerged as a potential solution to this problem: by looking at unique characteristics of the transmitter hardware expressed as impairments on the physical layer radio signal, transmitters can be differentiated from one another. Crucially, this can also separate legitimate transmitters from attacker-controlled SDRs, enabling robust authentication even in the absence of cryptography. At its face these systems grant enhanced security, but it is not known to what extent they are vulnerable against direct attacks on the fingerprinting system itself – existing evaluations of attacks are limited to simple replay and jamming [1–3], or make use of prohibitively expensive Arbitrary Waveform Generator (AWG) hardware [4].

In this paper we provide the first end-to-end evaluation of wireless fingerprinting under optimized jamming, spoofing, and poisoning attacks, assessing the extent to which these systems are vulnerable to attackers equipped with offthe-shelf hardware. We focus on the satellite use case due to the particular relevance of fingerprinting in this area – legacy satellites are uniquely both vulnerable to attacks on the wireless channel and prohibitively expensive to upgrade or replace, making fingerprinting a particularly appealing countermeasure. In undertaking this work, we can better understand the risks associated with fingerprinting alongside its benefits, enabling operators to make well-informed decisions surrounding its implementation.

Our experiments demonstrate that optimized jamming signals can cause significant disruption, even at very low amplitudes, and that spoofing signals can be constructed to make messages from one transmitter appear to come from another. We also show that attackers can mask out the fingerprint of their own transmitting hardware when replaying messages, and that reference messages can be poisoned over time through incremental updates, allowing an attacker-controlled transmitter to be accepted as legitimate. The implications of these findings are significant, highlighting the potential for fingerprinting systems to be vulnerable to targeted attacks, and the importance of using fingerprinting alongside other countermeasures. We also explore the use of Generative Adversarial Networks (GANs) to improve the security of fingerprinting systems, demonstrating that a GAN-trained discriminator can match the performance of state-of-the-art models at detecting replay attacks, even from previously unseen transmitters. Alongside detecting attacks, this technique also enables fingerprinting in systems with only a single transmitter – rather than training on a dataset with many different transmitters, operators can instead train a model using our SDR transmitreceive loop to differentiate between legitimate and malicious communication. This will enable operators of small constellations, or even single satellites, to gain additional protection against attacks by deploying fingerprinting as an additional countermeasure, without requiring a huge dataset containing many transmitters.

2. Background

In this section we introduce fingerprinting as a concept, looking in particular at its use in a satellite context and the difficulty of deployment in this area. We also introduce GANs and dataset poisoning attacks. Finally, we explore related work, looking in particular at adversarial attacks on fingerprinting, and similar attacks in the context of biometric systems.

2.1. Fingerprinting

Wireless fingerprinting enables the authentication of transmitters by extracting characteristics of the transmitter as expressed in the physical layer signal. These can be compared to previous messages to verify that they match, and that the message was therefore sent by the legitimate transmitter rather than an SDR-equipped attacker.

There is already a large base of existing research in radio transmitter fingerprinting [5], with techniques including transient fingerprinting (looking at the start of the signal) [6] and steady-state fingerprinting (looking at the modulated data portion) [7], and extracting features by combining low sample rate messages [8, 9], looking at high frequency features [10], extracting features from the frequency domain [11], and more. These have been applied to a wide range of terrestrial systems including RFID [12], the ADS-B air traffic control system [13], Bluetooth [14], and WiFi [15].

Fingerprinting is particularly useful in satellite systems due to their heavy reliance on wireless communication and the immense difficulty of repairs or upgrades once deployed: in this environment, fingerprinting can provide authentication on the downlink without any changes to the satellite platform itself. However, fingerprinting is also more difficult in satellites due to the high degree of atmospheric distortion and attenuation, masking transmitter characteristics and requiring specialized techniques to overcome. This has been explored by some recent works, looking in particular at the GPS navigation satellites [7] and the Iridium constellation [8, 16, 17]. Among these, our experiments look in particular at SATIQ as the code, dataset, and model have been made available [16], making it easy to adapt to an adversarial context. Alongside an increased interest from an academic perspective, fingerprinting has also gained the attention of the commercial and public sectors: the European Space Agency (ESA) have recently allocated funding to explore applications for fingerprinting in the satellite context [18], and in 2021 Expedition Technology were awarded a contract by DARPA (USA) to expand their RF fingerprinting and spectrum characterization capabilities [19].

2.2. Generative Adversarial Networks

Generative Adversarial Networks (GANs) are a popular technique for image generation [20], and can be adapted to work in other contexts. The architecture is characterized by the combination of two components: a *generator*, which creates adversarial data, and a *discriminator*, which must tell the difference between legitimate and generated data [21]. Both of these are trained at the same time so that, over time, the discriminator gets better at telling real and generated data apart, thus forcing the generator to get better at synthesizing realistic data. We adapt this architecture to work with radio signals, training a GAN to generate signals that remove the fingerprint of an attacker-controlled SDR.

2.3. Poisoning Attacks

Data poisoning attacks involve the introduction of malicious data into a model, affecting its downstream operation [22–25]. These attacks can take place during the training phase, adding false data into the training dataset in order to reduce performance, increase misclassifications, or falsely accept specific inputs. Alternatively, they can take place during operation, altering the ground truth over time through the gradual introduction of adversarial examples – this is particularly effective in biometric systems, where inputs are compared against previous data [26]. The presence of update mechanisms (which are often triggered by sufficiently large changes in the input) enables the attacker to gradually shift the ground truth against which new inputs are compared, such that a given target input is accepted.

Poisoning techniques are broadly transferable to the satellite fingerprinting context, although to the best of our knowledge no other works exist that specifically target satellite fingerprinting systems. We explore poisoning as an attack strategy in Section 4.5.

2.4. Related Work

The authors of [27] provide an overview of adversarial attacks on Radio Frequency (RF) machine learning systems. This includes attacks on signal and modulation classification systems [28–30], jamming attacks [31], and attacks on RF fingerprinting systems [32, 33]. In [32] a generalized approach is given for adversarial jamming and spoofing against a target neural network, and the authors demonstrate its effectiveness against a classifier for the "ADS-B" protocol used in aviation, and a signal modulation classifier. We use

a similar approach in this paper, using gradient descent to find optimized jamming signals. In [33], the authors instead use reinforcement learning techniques to fool a discriminator classifier into accepting messages from an attackercontrolled transmitter, based on binary classification alone, evaluating the approach using 8 SDRs. The desired outcome in this case is similar to our spoofing experiments, but we examine a much larger set of transmitters and focus on realworld systems. Finally, in [34] the authors use SDRs to gather a dataset for fingerprinting, but all imperfections are introduced at the software level, and the impact of the SDRs is not measured.

There has also been some work looking at direct impersonation of device fingerprints: the authors of [4] replay messages using an AWG, resulting in the duplication of transmitter fingerprints. In [1] a similar approach is attempted using SDR hardware at lower sample rates, with limited success. We further discuss the implications of the attacker's capabilities and hardware in Section 3.

Many of the attacks explored in related works are against classifier-based systems, with a particular focus on image classification [35]. In the case of classifiers, attacks naturally target misclassifications within the system. However, when targeting a distance-based system like SATIQ, attacks instead focus on the distance metric produced by the model, aiming to either increase the distance between legitimate samples and their anchors to create jamming behavior, or decrease the distance to known anchors to spoof messages or alter the fingerprint. This aligns more closely with adversarial research in biometric systems, in which there already exists a good amount of work. For instance, in [36] the authors use gradient descent to produce adversarial perturbations for misclassification in face recognition systems, and in [37] the authors use hill climbing (a similar approach) to find optimized attacks on a human fingerprint recognition system. Finally, in [38] the authors train a GAN to perform spoofing attacks on voice recognition systems, and discuss its usefulness as a countermeasure to these attacks. We explore similar approaches to each of these in our spoofing experiments later in this paper.

3. Threat Model

In this paper we consider a high sample rate fingerprinting system that has been deployed at a satellite ground system, to provide authentication for downlinked communication. An attacker may aim to disrupt the availability of this system, denying service through increased false rejections, or to disrupt authenticity by altering the identity of messages, causing their own transmitters to be falsely accepted. In particular, we look at the following attacks (illustrated in Figure 1):

Jamming. The attacker wishes to disrupt the availability of the system by altering the fingerprint of incoming messages. This can be achieved by adding a jamming signal to incoming messages, optimized to disrupt the fingerprint as much as possible within the attacker's power limitations. This



Figure 1: Illustration of each attack in the threat model. (i) Jamming: the attacker broadcasts a signal to disrupt a legitimate transmitter. (ii) Identity Shift: the attacker modifies an incoming signal to alter the fingerprint. (iii) Fingerprint Masking: the attacker transmits a replayed message, undoing the effect of their own transmitter fingerprint. (iv) Data Poisoning: the attacker adds malicious data to the fingerprinting system, causing their transmitter's fingerprint to be accepted without modification.

builds on prior works looking at jamming in fingerprinting systems [3, 39], moving from general jamming signals (such as Gaussian noise or modulated data) to targeted jamming optimized for the fingerprinting model.

Spoofing (Identity Shift). The attacker aims to change the perceived originator of the message, making it appear as though it has been sent from a different transmitter. This may involve overshadowing a message (or part of a message) and changing the transmitter ID, thus requiring the attacker to change the fingerprint to match the new transmitter. Alternatively, this may manifest as an "assisted attack", in which the attacker compromises a satellite that is attempting to impersonate other transmitter can assist the compromised satellite by shifting the fingerprint to match the spoofed messages.

Spoofing (Fingerprint Masking). The attacker transmits an arbitrary message from a ground-based SDR, preceded by a replayed or generated message header from the satellite they are spoofing, in an attempt to mimic the fingerprint. However, the fingerprint is altered by their transmitter hardware, so they must undo the effect of their transmitter's fingerprint in order for the message to be accepted.

Data Poisoning. The attacker replaces the anchor messages with their own messages – these are the messages the

fingerprinting system compares to incoming messages for authentication, so replacing them with anchors that match the attacker's transmitter means the fingerprinter will accept any messages sent by the attacker as legitimate. Depending on the poisoning process, the result can be inclusive (the victim's original hardware is accepted alongside the attacker's transmitter) or exclusive (the victim hardware is rejected, and only the attacker is accepted).

3.1. Capabilities

We assume the attacker has access to commercial offthe-shelf SDR hardware, an appropriate amplifier, and an antenna, allowing them to transmit signals within the vicinity of the victim ground station. The attacker is assumed to run their SDR at a sample rate at or below the sample rate used by the fingerprinting system -25 MS/s in our experiments.

It has already been established in related work that an attacker equipped with an AWG can perfectly replicate signals down to the fingerprint in an experimental setting [4], but due to the high cost of this hardware we consider it to be out of scope for this work. We instead primarily consider SDR hardware, which impairs the signal with its own unique fingerprint that must be counteracted in the case of spoofing attacks, making attacks significantly more challenging [1].

Since the attacker transmits messages over the air, we assume the attacker can achieve time synchronization with the victim receiver, enabling them to transmit targeted interference (for example, jamming signals) over the top of legitimate messages, or send their own messages and have them picked up at the victim receiver. However, they cannot achieve perfect synchronization at the symbol or phase level – to do so would require a feedback loop with the victim ground system, which is not feasible in an attack setting.

During poisoning attacks, we assume the attacker has some mechanism by which they can introduce malicious data into the fingerprinting system. This could be achieved using an AWG, or via an alternative side channel into the system itself (for example, if the machine hosting the fingerprint examples has been briefly compromised). Although this attack is initially more challenging, it has a much higher success rate in the long term: once the data has been altered to match the attacker's hardware, they do not need to worry about masking their own fingerprint, as it is being accepted with the same rate as any other transmitter. If inclusive poisoning is used, the victim's original transmitter will also continue to be accepted alongside the attacker's hardware, increasing the longevity of the attack.

Finally, for most experiments we assume the attacker to have access to the underlying weights of the fingerprinting model. This is a reasonable assumption to make in many cases, since for many existing fingerprinting systems the code, dataset, and model weights are openly available. However, even if the attacker does not have access to this data, it has been shown in previous works that the same attacks can be achieved by training a "surrogate model" on a similar dataset, executing the attacks on this model, and transferring the attack to the original system [25, 40]. We demonstrate a similar outcome through the use of a GAN in the "fingerprint masking" attack.

4. Experiment Design

In this section we design experiments to test each of the attacks described in Section 3. We start by describing some of the common methodologies used across experiments, before moving to the experiments themselves, and the hardware and software architectures used. The experiments and their parameters are summarized in Table 1. All datasets and trained models used in this paper will be made openly available on publication, in addition to the code needed to carry out all the experiments.

4.1. Experimental Foundations

We first outline the common methodologies and setups shared across the experiments described in this paper.

4.1.1. Base Fingerprinting Model. For each of our experiments, we use the trained SATIQ model available from [16]. This model takes message headers from Iridium transmitters at a sample rate of 25 MS/s and condenses them into a fingerprint, which is then compared to "anchors" (i.e., reference messages) for the given transmitter using cosine distance, giving a distance metric which is used to authenticate the transmitter, or reject illegitimate communication. Accepting or rejecting a message depends on the distance threshold set by the operator, and can be increased to make the system more strict, rejecting a higher proportion of illegitimate messages at the expense of accepting fewer legitimate messages, or decreased to make it more lenient. For the majority of this work we do not consider a specific threshold, but instead consider the distance as a raw value (or in some cases consider a range of thresholds), to give operators an insight into how setting the threshold affects the security of their system under each of the tested attacks.

4.1.2. Dataset. Alongside the model, we also use the dataset from [16], comprising Iridium messages from 66 satellites, each of which have 48 transmitters [41]. By using an already available dataset, we ensure both that the data is compatible with the model, and that the results can be easily reproduced. In all the experiments in this paper, all signals are generated at the same sample rate as the original dataset, 25 MS/s. They are then scaled to a consistent overall energy level, and the signal is rotated by a random phase offset between 0 and 2π , to mimic the difficulty of perfect phase synchronization at such a high sample rate.¹

4.1.3. Transmit/Receive Loop. In order to execute and test some of the attacks in this paper (particularly identity removal), the attacker needs to be able to measure the impact

^{1.} Note that only the attacker's additions are rotated in this manner – the original dataset corrects for phase offset, so the victim messages are not rotated.

TABLE 1: Parameters and variables for each of the experiments.

Variable	Values	Jamming	Identity Shift	Fingerprint Masking	Data Poisoning
Number of messages during training	1, 10, 100	1	✓ A		
Phase synchronization	True, False	1	1		
Attacker-to-victim power ratio	-75 dB to $5 dB$	1	1	\sim^{B}	
Filter signal	True, False	1	1	$\sim^{\rm C}$	
Victim messages all from same transmitter	True, False		1		
Fingerprinter acceptance threshold	$a \in [0, 1]$				1
Fingerprinter update threshold	$u \in [0, 1], u < a$				1
Inclusive poisoning attack	True, False				1

A: Due to dataset size limitations, 1, 16, 32 are used instead.

B: The attacker's modifications are transmitted alongside the original message, which is sent at a fixed power level.

C: The signal is not filtered in software, but a hardware filter is used during experiments.

of their own hardware on the signal fingerprint, with realtime feedback. We achieve this by building a transmitreceive loop composed of two SDRs connected to one another by a cable, so that arbitrary samples can be sent to the transmitting SDR, sent over the cable, and received at the other end with near-perfect time and phase synchronization. This can be used during training to learn the fingerprint of the SDR and how to counteract it, before deploying attacks over the air using the transmitting SDR only.²

By transmitting messages over a wire instead of over the air, we control for as many sources of noise and distortion as possible, ensuring the primary source of impairment is the fingerprint of the SDRs. Alongside increasing the difficulty of carrying out attacks, this has the added benefit of realistically filtering and attenuating signals. We do not need to worry about phase synchronization when using this setup, as the attacker is transmitting the message header and their own modifications simultaneously.

We use the following hardware:

- Ettus Research OctoClock-G CDA-2990
- $2 \times$ Ettus Research USRP X300 SDR
- 2× Ettus Research SBX-120 daughterboard
- Mini-Circuits VBF-1560+ filter
- Mini-Circuits BW-S30W20+ attenuator

The two SDRs are connected to each other via SMA cables, with the filter and attenuator between them, and are connected to an OctoClock to ensure time synchronization. Messages are preceded by a rising edge which is used to synchronize at the sample level, and a header with a known phase is used for phase alignment. The attenuator and filter protect the hardware from damage, and provide filtering characteristics matching the real-world receiver hardware.

On top of this hardware setup we provide an easy-to-use ZeroMQ interface, enabling software to send samples over a socket and receive those same samples after they have been sent through the transmit-receive loop. This is also incorporated into a TensorFlow layer, allowing the hardware loop to be used for dataset preprocessing or integrated into the model itself, enabling it to learn the characteristics of physical layer distortions and how to counteract them.

4.1.4. Filtering. Some of the experiments in this paper require signals to be filtered in software, in order to prevent unrealistic wideband interference. However, the SciPy signal processing functions are not differentiable by TensorFlow, so we reimplement the filter directly as a convolution over the signal. Whenever this filter is used in experiments, we use a Finite Impulse Response (FIR) filter with a cutoff of 0.333 MHz and 128 taps.

4.2. Jamming Attack

We start our experiments with a simple jamming attack, using gradient descent to find an optimized jamming signal. This moves beyond previous work looking at general Gaussian and tone jamming techniques on fingerprinting systems, instead optimizing for maximum disruption to the transmitter fingerprint [39]. This experiment is performed offline, using a trained fingerprinting model and captured data from Iridium satellites.

Our goal is to find a generalized jamming signal that works across many different messages which, when added to the synchronization header for a victim message, increases the distance from the message fingerprint to a reference anchor so that the message is rejected. To find this, we perform gradient descent directly on the samples of the jamming signal. At each step of gradient descent, we filter the jamming signal, normalize it so the attacker-to-victim power ratio matches a pre-defined value, and add it to the victim's signal. Finally, we define the loss function to maximize the distance between the fingerprint of the jammed signal and the fingerprint of the original victim signal.

To find a jamming signal that can be generalized across messages, we apply the jamming to a set of multiple different messages during training, taking the mean fingerprint distance of the resulting jammed signals when calculating loss. We also optionally rotate the jamming signal to a random phase offset after each use, forcing the gradient descent to produce a jamming signal that can work at any phase offset, and is therefore effective even when the attacker cannot achieve phase synchronization. The parameters for this experiment are given in Table 1.

^{2.} One caveat to this approach is that a trained model will learn the fingerprint of both the transmitting and receiving SDRs. The impact of the receiving SDR's fingerprint might be insignificant, but if the attacker wishes to remove the receiving SDR's fingerprint, they might use multiple receiving SDRs during training so there is no single consistent fingerprint for the model to learn.



Figure 2: Architecture of the "Siamese GAN" model used for the masking experiments. "SDR" represents the physical hardware transmit-receive loop.

To assess the performance of the attack, we apply the jamming signal to a new set of clean messages, separate from the training data used during gradient descent. We set the acceptance threshold (i.e., the distance between two fingerprints below which the message is accepted) such that 95% of legitimate messages are accepted,³ and look at the fingerprint distance and resulting False Rejection Rate (FRR) as the power of the jamming signal increases. We compare this to traditional Gaussian jamming on the Iridium decoder and on the fingerprinting system, by looking at the attacker-to-victim ratio required to cause a 50% error rate in each case.

4.3. Identity Shift Attack

Next we look at simple spoofing attacks, in which the attacker is trying to alter the fingerprint of legitimate messages to change their perceived identity. We assess this using similar methods to the jamming attack, performing gradient descent on the samples of a message, but with a modified loss function: instead of maximizing the fingerprint distance from the modified signal to the original message, we instead minimize the distance to a given set of target messages. The target messages all belong to the same transmitter, so the resulting modification attempts to both remove the original fingerprint and add the fingerprint of the target signal. We perform this attack using victim messages from the legitimate Iridium dataset, attempting to shift transmitter IDs from either a set of messages all belonging to the same transmitter, or random messages from any transmitter. These and the other experimental parameters are summarized in Table 1.

Similar to the jamming attack, we assess the effectiveness by looking at the change in fingerprint distance on a separate test dataset with previously unseen messages. The target messages are taken from the same class of target transmitter as was used in the training data, and the same is true of the victim messages. The test therefore measures how effective the attack is at modifying the fingerprints of the same transmitters it has seen during training, but using unseen messages to ensure the spoofing signal has not overfitted. Alongside looking at the distance between messages in fingerprint space, we also consider the False Acceptance Rate (FAR) of the spoofed messages, fixing the acceptance threshold such that 95% of illegitimate messages are rejected when no spoofing signal is present.

4.4. Fingerprint Masking Attack

We look next at spoofing attacks in which the attacker is directly transmitting their own messages, using synthesized or replayed message headers in order to impersonate a specific transmitter. In order to do this, they must learn to counteract the effect of their own SDR on the fingerprint such that it cannot be detected by the receiver.

In this experiment we start by using the same architecture and parameters as in the identity shift experiments, but first passing all the attacker's messages through the transmitreceive loop described in Section 4.1.3. This means that in order to be successful the attacker's signal must counteract the fingerprint of the SDRs.

We then build on this by using a full GAN architecture, training a discriminator to distinguish legitimate messages from those that have been replayed, at the same time as training a generator model to create convincing fake messages. We once again incorporate real-world SDR hardware into this experimental configuration by using the physical transmit-receive loop, forcing the generator to learn how to remove the impairments on the fingerprint added by the SDRs, at the same time that the discriminator is learning to detect them. The high-level architecture of this approach is illustrated in Figure 2, and the full model layers are given in Appendix A.

One beneficial side effect of this architecture is that it does not require access to the weights of the original model (as the discriminator is being trained from scratch), reducing the attacker's requirements. The trained discriminator may also be used as a fingerprinting system itself; we evaluate the efficacy of this fingerprinter in Section 5.5.

Once a model has been trained, we measure its effectiveness by taking a group of messages from the testing dataset, passing it through the GAN and the transmit-receive loop, and comparing the distance between the resulting messages in fingerprint space to a separate group of clean messages from the testing data.⁴ We also look at the effect of the transmit-receive loop only (without the corrections added by the GAN), and compare the effectiveness of the GAN's discriminator to the original fingerprinting model. We primarily assess the performance of the GAN by looking at the Receiver Operating Characteristic (ROC) curve, which plots the true positive rate against the false positive rate as the acceptance threshold changes. The Area Under Curve (AUC) indicates the overall performance across all

^{3.} This threshold can be adjusted to accept more legitimate messages at the cost of easier spoofing (or vice versa). We choose 95% as a good middle ground.

^{4.} Since our focus is on spoofing attacks, we look at pairs of messages belonging to the same transmitter as each other, one of which has been passed through the GAN.

thresholds, with 0.5 indicating random guessing. We also look at the Equal Error Rate (EER), the point at which the false accept and false reject rates are the same.

4.5. Data Poisoning Attack

Finally, we look at poisoning attacks. This technique is commonly used in biometric authentication systems, in which the examples used to authenticate new measurements are gradually replaced by adversarial samples, altering the behavior of the system so the attacker is accepted as legitimate. In this attack, we assume the attacker has access to the weights of the fingerprinting model (although similar results could likely be achieved by training a surrogate model on the original dataset [40]) and the messages originally used by the fingerprinter. As discussed in Section 3, we also assume the attacker has some mechanism by which they can introduce their adversarial samples into the fingerprinting system.

The fingerprinting system at the receiver is configured to accept messages whose fingerprint distance falls below a given threshold $a \ge 0$, and to replace anchor messages when the fingerprint falls between this threshold and a separate update threshold $u \ge 0$ (u < a). We attempt to construct a short sequence of messages such that no message is rejected by the fingerprinter, and resulting in acceptance of the attacker's messages by the end of the sequence. This mirrors the behavior of previous attacks on biometric systems [26], and generating adversarial inputs that fall between these two thresholds is a key challenge in poisoning attacks. Other update conditions are not considered in this work, but given a different condition it would be straightforward to update the algorithm to generate messages which satisfy it.

Although autoencoders can permit simple interpolation, the specific architecture of SATIQ raises some issues with this technique; the decoder and encoder are not perfect inverses of one another, so interpolation can result in waveforms whose fingerprints differ quite significantly from one another, particularly at the start and end of the chain. We instead find that attacks are more successful if only the encoder is used, with a sequence of steps making use of gradient descent on the raw samples in the waveform. At each step i, we perform gradient descent starting from the previous message S_i , looking for a new message header S_{i+1} which satisfies the following conditions:

$$u < \operatorname{dist}(e(S_i), e(S_{i+1})) < a$$

$$\operatorname{dist}(e(S_i), e(S_N)) - \operatorname{dist}(e(S_{i+1}), e(S_N)) > u$$

Where *e* is the fingerprint encoding function, dist is the distance function, *a* and *u* are the acceptance and update thresholds for the fingerprints, and S_N is the target. A message header which satisfies these conditions will, at each step, be accepted by the fingerprinter and trigger an update to the anchor message. These conditions are used as the exit condition for the gradient descent, and the loss function has two corresponding components: one to encourage dist $(e(S_i), e(S_{i+1}))$ to be between *u* and *a*, and another to



Figure 3: Results (mean fingerprint distance and false rejection rate) from the jamming experiments, when the attacker does not have phase synchronization. False rejection rates are given relative to an initial threshold set such that 95% of messages in the attack-free dataset are accepted.

encourage dist $(e(S_{i+1}), e(S_N))$ to be as small as possible. This enables us to iteratively move the fingerprint closer to the target, until the final step at which the target's messages are accepted.

The following update condition (with corresponding loss component) can also be added to the process:

$$\operatorname{dist}(e(S_{i+1}), e(S_0)) < a$$

This results in an "inclusive poisoning" attack, in which both the attacker and victim transmitter are accepted as legitimate. Although the attack is harder to execute due to stricter update conditions, the result is more subtle, since the original victim transmitter is no longer rejected by the fingerprinting system, in addition to the attacker's messages getting accepted. The attack is therefore more likely to persist for longer without being corrected.

We assess the effectiveness of poisoning by looking at how many steps it takes to get between two messages. We consider the attack to have failed if it takes more than 50 steps, or if the gradient descent does not find a suitable next step within 1000 iterations.

5. Results

In this section we analyze the results of each of the experiments described in Section 4. Although we ran experiments under all the given configurations, due to space constraints we focus on the most interesting results; the remaining results can be found in Appendix B.



Figure 4: Examples of some of the signals produced by the jamming attack.

5.1. Jamming

We start by looking at the jamming attacks described in Section 4.2; these are summarized in Figure 3.5 We can see that even at very low amplitudes it is easy to generate adversarial perturbations that disrupt the victim's fingerprint, with or without a filter applied to the signal (although the inclusion of a filter does impede performance slightly). We also see that by training the jamming signal on a larger number of example messages, performance is improved on unseen messages not present in the training data. In all cases, the jammer significantly exceeds the performance of traditional Gaussian jamming techniques evaluated in prior works [39]. In these, an attacker-to-victim power ratio of approximately -3.0 dB is required to cause a 50% error rate on the Iridium decoder, and approximately $-2.7 \, \text{dB}$ on the fingerprinting system. In contrast, we can see that our optimized jamming signal only requires approximately -40 to -30 dB – this is well below the noise floor, making the attack very difficult to detect. In practice, the attacker may wish to increase the amplitude of their jamming signal higher than strictly necessary in order to ensure effectiveness in a noisy environment with high levels of attenuation, particularly when they lack any feedback regarding the success of the attack.

Alongside its effectiveness this technique is also versatile, requiring no real-time input of the victim signal or generative capabilities to jam communication. Real-time reactive jamming has been shown to be technically feasible [42], but it is difficult and requires high-end hardware; it is much easier to prepare a jamming signal in advance and broadcast it in time with the message header. We can see from the results that the characteristics of optimized jamming signals are largely message- and transmitter-agnostic, so the attacker does not need to capture the message in real time, and can instead cause significant disruption by using a generalized jamming signal.

Looking at the actual jamming signals produced by this technique, they appear to converge upon a number of



Figure 5: Initial results from the identity shift attack, on messages from the legitimate dataset. False acceptance rates are given relative to an initial acceptance threshold, set such that 95% of illegitimate messages are rejected.

different jamming modes, illustrated in Figure 4:

- In the first mode, the jamming signal produces a highamplitude burst over a short period of time. The time of the burst can vary, but appears to be aligned with symbol transitions.
- In the second mode, the waveform has more consistent noise overall, punctuated by some bursts of noise which appear to resemble a QPSK-modulated constellation, matching the modulation scheme used by Iridium.
- In the third mode, noise is even more consistent across the message, with "swirl" patterns that vaguely resemble tone jamming.
- In the final mode (which only emerges when phase alignment is enabled), sharp bursts are aligned with the I and Q axes to produce maximal offsets.

We also note that the short impulses used in the final jamming mode may be ineffective in practice, due to the presence of filters on the receiver. They do, however, help confirm the theory that fingerprint information is derived from the transitions between symbols, as the jamming impulses are aligned with these sections.

5.2. Identity Shift

Next we look at the identity shift attack described in Section 4.3. We can see the initial results of these experiments in Figure 5, with a single spoofing signal optimized to modify messages from one transmitter so their fingerprint looks like

^{5.} Results when the attacker can achieve phase synchronization with the victim can be found in Appendix B.1, but are not discussed here as the performance is very similar.



Figure 6: Distance in fingerprint space for messages from legitimate transmitters, compared to messages sent through the SDR transmit-receive loop, and messages generated by the GAN. Tested on the original SATIQ discriminator (left) and the GAN's discriminator (middle), in addition to error curves for each model on the generated data (right).



Figure 7: Results from the simple fingerprint masking attack, using gradient descent to find a single optimized spoofing signal. False acceptance rates are given relative to an initial acceptance threshold, set such that 95% of illegitimate messages are rejected.

another.⁶ We can see that as the attacker power increases, there is a measurable decrease in the distance to the target fingerprint, showing that identity spoofing is possible. This is not the case when only one training message is used; multiple messages are required in order to correctly learn the fingerprint characteristics. In the best case, the attack lacking phase synchronization achieves a 12.3% FAR. When

6. Similar to the jamming experiments, testing data is entirely separate from the training data.

phase synchronization is permitted, this improves to 31.4%, suggesting the fingerprint of messages is not phase invariant; however, this does not match our threat model, since it is unlikely for the attacker to be able to synchronize perfectly with the victim message. We also see that although optimal performance is achieved at the highest power levels, good performance can still be achieved at lower amplitudes, so the original message does not need to be overshadowed entirely. Examples of the spoofing signals produced by the attacks can be found in Appendix B.2, as well as further results, particularly for experiments in which the messages are not filtered, and those in which the starting samples are random (i.e., from different transmitters) rather than all belonging to the same transmitter. In both these cases, attack performance is worse due to the increased difficulty of the attack.

5.3. Fingerprint Masking

First we look at the simple masking attack, using the same architecture as in the identity shift attacks but with SDR-replayed messages, using the experimental setup from Section 4.1.3. This creates a more realistic attack model, in which the attacker is not only trying to shift the identity of a specific transmitter, but also to undo the effect of their own SDR. The results for this attack are in Figure 7, with full results in Appendix B.3. In these results, the starting fingerprint distance is measurably higher than in the identity shift attack, since the SDR hardware in the loop has imparted its own additional fingerprint upon the signal, which must be removed. For this reason, the initial FAR with no corrections applied is close to 0%. Despite this, the generated spoofing signal is able to counteract this, with a peak FAR of 10.0%, or 29.6% when phase synchronization is permitted.

Next we look at the results from the GAN, in which the generator is learning to counteract the SDR fingerprints at the same time as a generator is being trained to distinguish the attacker from legitimate data. These results can be seen



Figure 8: A selection of the steps involved in poisoning by interpolating between the fingerprints of two legitimate transmitters. To save space, not all steps have been shown.



(a) "Exclusive" poisoning: original anchor not included in the target.

(b) "Inclusive" poisoning: original anchor included in the target.

Figure 9: Number of steps required to poison the reference fingerprints to accept one transmitter instead of another, given the acceptance threshold and update threshold.

in Figure 6, in which we take a set of base messages from legitimate transmitters, and compare their distance in fingerprint space to legitimate messages, those that have been passed through the transmit-receive loop, and those created by the GAN's generator. We can see from these that the SDRs alter the fingerprint to some extent, which the GAN is able to counteract, ultimately resulting in a ROC curve with an AUC of 0.6553 and EER of 0.3909.

We can also see that it is very easy for the discriminator from our newly trained GAN to separate the legitimate messages from those passed through the SDR loop, and the effect of the generator on its effectiveness is near-negligible – it can identify the attack with an EER of less than 0.00001. This suggests there is a clear fingerprint attached to the SDR which can be detected with explicit training, but that the SATIQ model struggles to detect, due to having only been trained on legitimate Iridium transmitters.

Training a GAN with transmit-receive hardware in the loop opens up some interesting new possibilities in the realm of single-transmitter fingerprinting. Since the GAN's discriminator has been trained directly to detect spoofing attacks, rather than gaining this ability as an incidental side effect of training to distinguish between legitimate transmitters, it demonstrates much better performance when detecting attacks. We evaluate this further in Section 5.5, and discuss how this can be used in practice to secure singlesatellite systems, enabling fingerprinting techniques to be used outside the realm of large satellite constellations.

5.4. Poisoning

Finally, we look at the poisoning attacks described in Section 4.5, in which the anchors are gradually updated to include the fingerprint of an attacker-controlled SDR.

We start by demonstrating the technique on legitimate messages from the training dataset, poisoning the fingerprinter such that it recognizes transmitter B as transmitter A. An example of the steps in this process can be seen in Figure 8. In this figure we can see the noise-removing effect of the fingerprinter's autoencoder: even though the final waveform generated by this process has more noise than the target waveform, the fingerprints are still highly similar to one another. We also see that, similar to the jamming and spoofing experiments explored earlier, altering the fingerprint does not require a signal with a huge amplitude, and the use of a low-pass filter does not impede performance (although it does produce substantially different-looking adversarial signals). Interestingly, the signal does not need to be higher amplitude in the filtered case. In order to produce



Figure 10: A selection of the steps involved in interpolating between a legitimate transmitter's fingerprint and a random fingerprint. To save space, not all steps have been shown.



Figure 11: The distance, in fingerprint space, from each step in the poisoning process to the initial/target/previous step. Distances are shown for exclusive and inclusive fingerprinting.

properly optimized signals, the attacker will need to obtain the approximate parameters of the receiver so the generated messages properly match.

The poisoning technique can be repeated for any acceptance threshold and target threshold; Figure 9 illustrates the number of steps required for a range of thresholds.⁷ Note that the process is more difficult (either taking more steps or failing to converge entirely) if the thresholds are very close to one another, or if the acceptance threshold is sufficiently low. Similarly, if the acceptance threshold is below approximately 0.3 and inclusive poisoning is used, the technique fails to find a next step and fails. If the acceptance threshold is too low, then the fingerprints of two different transmitters are sufficiently far apart that it is not possible to find an anchor that includes both the victim's original transmitter and the attacker's transmitter, making inclusive poisoning impossible. We can also see this in Figure 11, where we see that the distance to the initial/target fingerprint are very similar for both exclusive and inclusive poisoning, but the inclusive strategy is forced to terminate earlier as it fails to find a suitable next step. Despite this,

TABLE 2: Performance of the newly trained GAN discriminator compared to the original SATIQ model, for each of the tested datasets.

Discriminator	Attack	AUC	EER
GAN SatIQ	Transmit/Receive GAN Replay Transmit/Receive GAN	0.9999 0.9999 0.8094 0.6553 0.6224	0.0007 0.0001 0.2605 0.3909 0.4191
	Replay	0.8399	0.2564

an attacker may be able to use inclusive poisoning when the acceptance threshold is sufficiently high, and in other cases may take advantage of inclusive poisoning to evade detection for longer – the initial stages of poisoning can be completed inclusively to evade detection, switching only to exclusive poisoning when forced to do so.

Finally, we demonstrate that this poisoning attack can work on arbitrary data and fingerprints, even those that do not resemble any legitimate transmitters seen by the model during training. We show this by generating a random fingerprint and poisoning the reference fingerprints so the model recognizes this false transmitter as legitimate. An example of this can be seen in Figure 10. Note once again that the final message differs quite noticeably from the generated poisoning samples, likely due to the denoising effect of the fingerprinter. This works in the attacker's favor, as they do not need to necessarily send messages which resemble the target fingerprint at first glance.

Through these results we have shown that the fingerprinter can be poisoned to accept any target transmitter as legitimate, by injecting a short sequence of controlled messages to guide the reference anchors away from the original transmitter. This can certainly be achieved using an AWG, but it remains to be seen whether off-the-shelf SDR hardware could deliver the same result. In Section 6 we discuss improvements to the fingerprint update function which might mitigate this attack.

5.5. Single-Transmitter Fingerprinting

Alongside optimized spoofing attacks, the architecture of the GAN-based attack in Section 5.3 also opens up new opportunities in the area of single-transmitter fingerprinting.

^{7.} To ensure computation finished in a timely manner, gradient descent was aborted after 1000 iterations if a suitable next step was not found.



Figure 12: Distance in fingerprint space for messages from legitimate transmitters, compared to messages from the replay dataset provided in [16]. Tested against the original SATIQ discriminator (left) and the GAN's discriminator (middle), in addition to error curves for each model on the generated data (right).



Figure 13: ROC curves showing performance of the GAN and SATIQ model at distinguishing legitimate communication from attacker-replayed communication in each dataset.

Unlike the original SATIQ model, which has learned how to detect spoofing attacks as a side effect of learning to distinguish between legitimate transmitters, the GAN has been trained directly to detect spoofing attacks, so its performance is significantly better. We validate this by testing the model on the message replay dataset used to test SATIQ, which was created using completely different hardware from the experiments in this paper [16].

The results of this analysis can be seen in Figure 12, with ROC curves in Figure 13. Results are summarized in Table 2. From these we see that in addition to detecting the spoofed messages from its own training loop with nearperfect accuracy, the GAN also displays comparable performance to SATIQ on the replay dataset, from transmitters it has never seen before. On this data, it achieves an AUC of 0.8094 and EER of 0.2605 – only a slight performance drop from SATIQ's EER of 0.2564, despite having only been trained on a single attacker transmitter.⁸ Importantly, this is achieved without ever having seen replayed messages from this test transmitter during training, giving us confidence that the model will protect against a wider range of attackers than just those seen in the training data.

This result opens the door for fingerprinting on individual satellites: instead of gathering a dataset from a whole constellation of satellites, operators can instead collect messages from a single transmitter, and train a model to distinguish between these messages and an attacking SDR. This could be done in the lab and even updated on the fly to incorporate different SDRs or to add new transmitters to the system; we discuss this further in Section 6. This lies in contrast to all previous works, which focus on larger constellations with many transmitters, and cannot be used to secure individual satellites or transmitters. A "conditional GAN" architecture [21] could also be used to bridge the gap to providing transmitter-specific authentication in a small constellation, given a sufficiently large dataset of legitimate messages from each transmitter. With recent increases in attacks on satellite systems, even those equipped with cryptographic security, any additional authenticity and signal intelligence that can be applied on top of existing systems is invaluable. By expanding the scope of previous works, our results enable the detection and mitigation of attacks even on individual satellites, thereby providing more robust and resilient communication and enhancing the overall security of satellite-dependent infrastructure.

6. Discussion

The experiments presented in this paper have demonstrated the vulnerability of satellite fingerprinting to various attacks, including jamming, spoofing, and dataset poisoning. While these attacks can be effective, there are some

8. Note that the results here compare against only a single anchor; performance can be improved further by using multiple anchors [16, 17].

limitations and potential mitigations that can be explored. For instance, comparing incoming messages against multiple reference anchors or taking a rolling average from multiple messages can reduce the false rejection rate and make attacks more difficult to execute, requiring the attacker to synchronize their signal to multiple messages in a short time period in order to have a significant effect. The presence of filters in standard receiver hardware may also affect attacks, although our results show that including these filters in the adversarial training pipeline enables attacks to remain effective with a minimal performance drop.

There are also a number of countermeasures which may be deployed to protect against attacks. One approach to protect against dataset poisoning is to prevent attackers from controlling when anchors are updated, which could be achieved by triggering updates manually within a given time window, or by randomly choosing anchors from the most recent N messages sent from a given transmitter. This can make poisoning attacks substantially more difficult to execute, requiring persistent effort from the attacker over an extended period of time.

Another approach to countering attacks is to combine multiple sources of signal intelligence to provide improved coverage against attacks. Although the optimized attacks in this paper are effective against the fingerprinting system tested, they may be detected by a different mechanism – for example, the high-amplitude bursts exhibited by some of the jamming signals in Section 5.1 could be identified by monitoring the signal-to-noise ratio over time. By combining multiple methods, satellite communication systems can left without a single point of failure.

The single-transmitter fingerprinting techniques discovered in this paper offers another promising countermeasure against spoofing and replay attacks. By training a model directly on detecting spoofing attacks, it can be more effective in this area, even when the specific attacker SDR was not present in the training dataset. Alongside enabling fingerprinting in smaller satellite systems, this technique also opens up the opportunity for centralized training: a single SDR loop system can be used to train many models at once, targeting different satellite systems. This could even result in system-agnostic fingerprinting, with a model trained to detect attacks regardless of the underlying signal modulation scheme.

Finally, we can draw inspiration from existing systems in their approach to countering attacks [27, 35]. These include training classifiers on an augmented dataset containing adversarial examples ("adversarial training") [43, 44], or using techniques like randomized smoothing and defensive distillation to smooth gradients, thus reducing the attacker's ability to find adversarial perturbations [29, 45, 46]. Preprocessing techniques are also proposed, such as training an auxiliary detection model to remove adversarial perturbations prior to the classifier [30, 47–49] (optionally also taking into account characteristics of the physical RF channel [50]) or using an ensemble of classifiers to counteract one another's weaknesses [51]. Finally, "certified defense" attempts to verify that a model cannot be attacked by adversarial inputs, providing a certificate that proves that no adversarial perturbation below a given amplitude can result in more than a given level of misclassification on the test data [52] – this has been demonstrated on wireless signal classifiers [29]. Many of these techniques work with distance-based systems, or could easily be adapted to do so, and could therefore result in significantly more robust satellite fingerprinting systems.

By learning from these systems and combining multiple countermeasures, satellite communication systems can be made more resilient to attacks.

6.1. Future Work

Ultimately, our results show that no single security measure can be immune to attacks, and highlight the need for continued research and multi-faceted countermeasures. Future work should therefore focus on developing and evaluating combined countermeasures to provide broad coverage against various types of attacks. Additionally, the development of standardized testing frameworks would enable operators to assess their systems' resilience against different types of attacks in a consistent and reliable manner, and deploy new countermeasures.

Future work might also expand the scope of our experimental setup. For example, when carrying out our hardware experiments, we do not employ a channel model between the transmitting and receiving SDRs. This is not a major limitation, as the messages sent from the original satellite have already been impaired by the wireless channel. The attacker's signal is added on top of this, followed by some small distortion from the wired channel. It is important to distinguish between the impairments from the original satellite channel and those from the attacker's channel, as they have distinct characteristics - the attacker's channel is likely to have a much smaller degree of attenuation, particularly if the attacker is transmitting close to the victim receiver. Although the absence of a channel model does not significantly impact results, it may be interesting for future work to explore how a channel model might impede performance, and to see if a GAN can learn to counteract the SDR's fingerprint in the presence of greater levels of channel distortion. This can be achieved using specialized hardware, such as Keysight's "F8820A PROPSIM FS16 Channel Emulator". By attaching this hardware inline with the rest of the experimental hardware, varying levels of attenuation and fading can be added to the signal in real time.

7. Conclusion

In this paper we have demonstrated a wide range of optimized attacks against satellite fingerprinting systems with high performance. Optimized jamming attacks enable effective denial of service to fingerprinting-based authentication, even with very low amplitude perturbations, and spoofing attacks enable the reported identity of messages to be changed to match other transmitters, or for the fingerprint of an attacking SDR to be masked out entirely. Finally, through dataset poisoning we present a mechanism by which reference anchors can be gradually modified such that attacker-controlled transmitters are accepted as legitimate. By demonstrating these threats, we underscore the need for robust security measures in satellite communication, and the importance of combining multiple sources of signal intelligence in order to achieve broad coverage against attacks.

Alongside these, we have also introduced new countermeasures to attacks: a GAN trained for optimized spoofing attacks can be repurposed to instead detect spoofing attacks with high performance, even against transmitters it has never seen before. This advancement also enables single-transmitter fingerprinting – a technique previously thought to be infeasible due to the requirement of multiple transmitters in the training data. This represents a significant step forward in enhancing the resilience of satellite systems, offering a vital security improvement to legacy systems that lack cryptographic protection, and providing additional attack detection capabilities for newer systems.

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Appendix A. GAN Layers

Figure 14 shows the structure of the GAN model used in the fingerprint masking experiments, described in Section 4.4. The *Generator* takes message headers and generates modifications designed to remove the fingerprint of the SDR hardware. The *TxRxGenerator* takes these modifications, adds them to the original message, and passes the result through the transmit-receive loop. The *Embedder* takes a message header and reduces it to a lowerdimensional fingerprint. A discriminator is constructed using the embedder, computing the angular distance between a pair of embeddings.

Taking the generator g and discriminator d, we then build two loss terms:

- For any given input *i*, the generator loss minimizes d(i, g(i)), the distance between the input and the input following the generator.
- For two inputs i_a and i_b , the discriminator loss encourages $d(i_a, g(i_a))$ to be close to 1 and $d(i_a, i_b)$ to be close to 0.

Appendix B. Extended Results

In this appendix we outline some of the additional results from our experiments which were not crucial to the paper.

B.1. Jamming: Phase Synchronization

Results for the jamming experiment when phase synchronization is enabled can be seen in Figure 15. These results are at best comparable to the original results, and in many cases produce worse performance, particularly at higher power levels. It is likely this is caused by overfitting, with random phase shifts serving to force the jamming signal to be more generalizable – this means the attacker does not need to worry about phase alignment, and can simply generate a jamming signal and align it at the symbol level.

B.2. Identity Shift

Full results for the identity shift experiment under each configuration are given in Figure 17. We can see that performance is improved significantly when phase synchronization is permitted. Interestingly, we also see that performance is not greatly affected by the choice of starting transmitter (random, or from the same specific transmitter), suggesting that the attacker's signal can add a new fingerprint without having to worry too much about counteracting the original fingerprint – once transmit power is high enough, the attacker's signal dominates the old data.

Examples of the signals generated by these techniques can be seen in Figure 16. These once again make use of higher-amplitude bursts, albeit with more activity elsewhere in the waveform in order to affect the fingerprint as a whole.

B.3. Fingerprint Masking

Full results for the fingerprint masking experiment using the fixed spoofing signal (i.e., without using a GAN) are given in Figure 18. Results are comparable to the corresponding identity shift experiments.



Figure 14: Layers of each of the components involved in the GAN.



Figure 15: Results (mean fingerprint distance and false rejection rate) from the jamming experiments, when the attacker can achieve phase synchronization with the victim. Acceptance threshold is set such that 95% of legitimate messages are accepted.



Figure 16: Examples of some of the signals produced by the identity shift attack.



Figure 17: False Acceptance Rate for the identity shift experiments under each configuration, as the power of the spoofing signal increases. False acceptance rates are given relative to an initial acceptance threshold, set such that 95% of illegitimate messages are rejected.



Figure 18: False Acceptance Rate for the fingerprint masking experiments under each configuration, as the power of the spoofing signal increases, when a GAN is not used. False acceptance rates are given relative to an initial acceptance threshold, set such that 95% of illegitimate messages are rejected.