An assessment of automatic speaker verification vulnerabilities to replay spoofing attacks

Artur Janicki, Federico Alegre and Nicholas Evans

Abstract—This article analyses the threat of replay spoofing or presentation attacks in the context of automatic speaker verification (ASV). As relatively high-technology attacks, speech synthesis and voice conversion, which have thus far received far greater attention in the literature, are probably beyond the means of the average fraudster. The implementation of replay attacks, in contrast, requires no specific expertise nor sophisticated equipment. Replay attacks are thus likely to be the most prolific in practice, while their impact is relatively under-researched. The work presented here aims to compare at a high level the threat of replay attacks to those of speech synthesis and voice conversion. The comparison is performed using strictly controlled protocols and with six different ASV systems including a state-of-the-art iVector/probabilistic linear discriminant analysis system. Experiments show that low-effort replay attacks present at least a comparable threat to speech synthesis and voice conversion. The paper also describes and assesses two replay attack countermeasures. A relatively new approach based on the local binary pattern (LBP) analysis of speech spectrograms is shown to outperform a competing approach based on the detection of far-field recordings.

Index Terms—speaker verification, spoofing, presentation attack, replay, countermeasures, local binary patterns.

I. INTRODUCTION

Spoofing, also known as a presentation attack, refers to the projection of a falsified or manipulated sample to the sensor of a biometric system in order to provoke a high score and thus illegitimate verification. In recent years the automatic speaker verification (ASV) community has started to investigate spoofing and countermeasures actively [1], [2]. A growing body of independent work has demonstrated the vulnerability of ASV systems to spoofing through replayed speech [3], [4], impersonation [5], [6], voice conversion [7], [8], speech synthesis [9], [10] and attacks with non-speech, artificial, tone-like signals [11], [12].

Common to the bulk of previous work is a focus on attacks which require either specific expertise, e.g. impersonation, or high-level technology, e.g. speech synthesis and voice conversion. Only replay attacks can be performed with ease,

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requiring neither specific expertise nor sophisticated equipment; they are easily implemented with discreet, high-quality audio equipment, now available to the masses. Accordingly, it is reasonable to assume that replay attacks represent a tangible threat and that they, rather than speech synthesis and voice conversion will be the most prolific in practice.

Only few studies have addressed replay. The work in [3] assessed the vulnerabilities of a hidden Markov model (HMM) based, text-dependent ASV system using concatenated digits. While results showed that replay attacks are highly effective, experiments were conducted with data collected from only two speakers. The work in [4] investigated replay using recordings collected with close-talk or far-field microphones which are then replayed over an analogue or digital telephony channel. The work was conducted with data collected from five speakers and demonstrated the vulnerability of a joint factor analysis (JFA) ASV system; the false acceptance rate (FAR) at the equal error rate (EER) threshold increased from 1% to almost 70%. The authors in [13] investigated a text-dependent ASV system which was subjected to speech replayed using a laptop computer. Using the large, standard and publicly available RSR2015 corpus, this work showed that the EER for an HMM system increased from approximately 4% to more than 20%.

Missing from the literature, however, is a reliable comparative assessment of replay attacks to speech synthesis and voice conversion using large, standard databases and using a representative range of replay scenarios. Such a study is needed in order to help prioritise future work to develop countermeasures for the protection of ASV from spoofing. While well-intentioned, the work concerning speech synthesis and voice conversion attacks (including that of the authors), may have over-exaggerated the threat given that only few people have the necessary capabilities to implement them. Meanwhile, without appropriate countermeasures, ASV systems may remain vulnerable to replay attacks which are implemented much more easily. This paper accordingly aims to assess ASV vulnerabilities to replay attacks using the same ASV systems and corpora used in previous assessments involving speech synthesis and voice conversion. In addition, the paper investigates the effectiveness of new countermeasures which aim to distinguish between genuine and replayed speech.

The paper is organised as follows. Section II describes speech synthesis and voice conversion spoofing attacks with a comparison to replay attacks. Specific implementations used for the work reported here are also described. Section III presents previous and ongoing work to develop countermeasures against replay attacks, including the authors'work using

the local binary pattern analysis of speech spectrograms. A common experimental framework for the assessment of both vulnerabilities and countermeasures is presented in Section IV. Results are presented in Section V. Priorities for future work are discussed in Section VI followed by conclusions in Section VII.

II. AUTOMATIC SPEAKER VERIFICATION SPOOFING

This section describes speech synthesis, voice conversion and replay spoofing attacks and specific implementations. In general, a spoofed speech signal $s(t)$ is generated using a speech signal $x(t)$ which is representative of another, target speaker. Whereas the input to a speech synthesis system is a text string, that to voice conversion originates from a third speech signal of a source speaker (spoofer) $y(t)$.

A. Speech synthesis

There is a large variety of speech synthesis algorithms, such as formant [14], diphone [15], unit-selection [16] and statistical parametric [17] based approaches, in addition to more recent deep-neural network architectures [18]. Whatever the approach, the aim is to generate intelligible, natural speech for a given text string c. In the context of spoofing, a synthetic speech signal is generated according to:

$$s(t) = g_{x(t)}(c), \tag{1}$$

where $g_{x(t)}$ denotes a text-to-speech mapping generated by a synthesis system with speech units or acoustic models extracted or learned from the speech signal of a target speaker $x(t)$. Today's state-of-the-art, unit-selection and statistical parametric approaches to speech synthesis can learn the mapping function $g_{x(t)}$ from the adaptation of well-trained background models using only modest or even small quantities of speaker-specific adaptation data [19].

Our approach to statistical parametric speech synthesis uses hidden Markov models following the approach described in [20]. The specific implementation uses the HMM-based Speech Synthesis System (HTS)[1] where speech signals are parametrised by STRAIGHT (Speech Transformation and Representation using Adaptive Interpolation of weiGHTed spectrum) features [21], Mel-cepstrum coefficients and the logarithm of the fundamental frequency (log F_0) with their delta and delta-delta coefficients. Acoustic spectral characteristics and duration probabilities are modelled using multispace distribution hidden semi-Markov models (MSD-HSMM) [22]. Speaker dependent excitation, spectral and duration models are adapted from corresponding independent models according to a speaker adaptation strategy referred to as constrained structural maximum a posteriori linear regression (CSMAPLR) [20]. Finally, time domain signals are synthesised from windows of 25ms with a step size of 5ms using a vocoder based on Mel-logarithmic spectrum approximation (MLSA) filters [23]. They correspond to STRAIGHT Mel-cepstral coefficients and are driven by a mixed excitation

[1] http://hts.sp.nitech.ac.jp/

signal [24] and waveforms reconstructed using the pitch synchronous overlap add (PSOLA) method.

Full details of the HTS approach to speech synthesis can be found in [20], [25], [26]. The same system has been used extensively by other authors in the study of ASV spoofing, e.g. [10], [27], [28], [29], [30].

B. Voice conversion

Voice conversion has been used to explore ASV spoofing since the late 90s [8]. Among many others, one particularly effective approach to spoofing involves so-called Gaussian-dependent filtering [31]. Here, the spoofing signal $s(t)$ (or $S(f)$ in the spectral domain) is generated by filtering at the frame level the speech signal of a spoofer's source signal $y(t)$. In the spectral domain it can be represented as follows:

$$S(f) = \frac{|H_x(f)|}{|H_y(f)|} Y(f) \tag{2}$$

where $H_x(f)$ and $H_y(f)$ are the vocal tract transfer functions of the targeted speaker and the spoofer respectively. $Y(f)$ is the spoofer's speech signal whereas $S(f)$ denotes the result after voice conversion. A time-domain, converted signal is recovered as follows:

$$s(t) = IFFT\left(\frac{|H_x(f)|}{|H_y(f)|}\right) * y(t) \tag{3}$$

where * denotes convolution. As such, $y(t)$ is mapped or converted towards the target in a spectral-envelope sense, and is sufficient to overcome most ASV systems [31], [32].

$H_x(f)$ is determined from a set of two Gaussian mixture models (GMMs). The first, denoted as the automatic speaker recognition (asr) model in the original work, is related to ASV feature space and is utilised for the calculation of a posteriori probabilities. The second, denoted as the filtering (fil) model, is a tied model of linear predictive cepstral coding (LPCC) coefficients from which $H_x(f)$ is derived. LPCC filter parameters are obtained according to:

$$x_{fil} = \sum_{i=1}^{M} p(g_{asr}^i | y_{asr}) \mu_{fil}^i \tag{4}$$

where $p(g_{asr}^i | y_{asr})$ is the a posteriori probability of Gaussian component g_{asr}^i given the frame y_{asr} and μ_{fil}^i is the mean of component g_{fil}^i which is tied to g_{asr}^i. $H_x(f)$ is estimated from x_{fil} using an LPCC-to-LPC transformation and a time-domain signal is synthesised from converted frames with a standard overlap-add technique.

Full details of the Gaussian-dependent filtering approach to voice conversion can be found in [31], [32], [33]. These works, by other authors, in addition to the authors' own past work [11], [34], [35] show that this particular approach is among the most effective in terms of spoofing [2].

Attack	Naïve impostor	Replay	Voice conversion	Speech synthesis
Input	impostor speech	target speech	impostor speech	text
Effort	zero	low	medium-high	high
Effectiveness	low	low-to-high	medium-high	high

TABLE I: Comparison of four different spoofing attacks in terms of input, required effort and effectiveness.
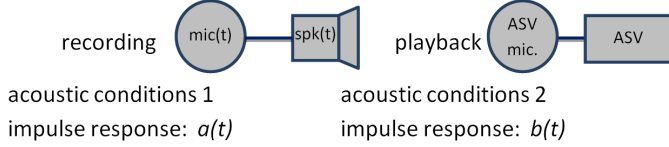

Fig. 1: A schematic diagram of the assumed replay attack configuration.

C. Replay

Replay attacks are an example of low-effort spoofing; they require simply the replaying of a previously captured speech signal. In the absence of suitable countermeasures and considering the widespread availability of consumer devices with high-quality sound systems, replay attacks can typically be realised with ease. Furthermore, used either directly, or through the cutting and pasting of short speech intervals, replayed speech has potential to overcome both text-dependent and text-independent ASV systems. Even though the processes of recording and replaying introduce additive acoustic and convolutive channel and transducer noise, these effects can be attenuated by noise and other intersession (channel) variability compensation techniques common to most modern ASV systems. These factors point towards the tangible threat posed by replay attacks.

Ignoring ambient noise in the acoustic environment (which is in any case not specific to the replay spoofing scenario), replayed speech can be represented as:

$$s(t) = x(t) * h(t), \tag{5}$$

where * again denotes convolution. The composite replay effects denoted by $h(t)$ include the impulse responses of capture and replay hardware in addition to those of the recording and replay environments. It is composed of:

$$h(t) = \text{mic}(t) * a(t) * \text{spk}(t) * b(t), \tag{6}$$

where $\text{mic}(t)$ and $\text{spk}(t)$ are impulse responses of the microphone and the speaker, respectively, and where $a(t)$ and $b(t)$ are the respective impulse responses of the recording and replay environments. This scenario is illustrated in Fig. 1. Replay attacks may thus be emulated through the convolution of a source signal $s(t)$ with typical impulse responses representing the different replay components.

Since an inordinately large number of different impulse responses would be needed to emulate representative replay attacks using Equation 5, a simplification can be applied to reduce their number. Since typical loudspeaker responses deviate more so from a regular impulse than typical microphone

responses, and thus dominate Equation 6, $\text{mic}(t)$ can be safely ignored. Furthermore, since $a(t)$ and $b(t)$ are similar in nature, a reasonable study can be achieved by considering only one. Thus:

$$h(t) \simeq \text{spk}(t) * b(t) \tag{7}$$

Equation 7 represents a worst-case scenario where the spoofer obtains a high quality recording of the target speaker's voice, with no recording artefacts. In this case, only replay components are considered and are the only means by which a replay attack can be detected.

D. Qualitative comparison

Replay, voice conversion and speech synthesis spoofing are forms of *concerted-effort* impostor attacks, as opposed to the naïve or *zero-effort* impostor attacks normally used to assess ASV system performance. A qualitative comparison of all four is illustrated in Table I, ordered by the level of effort or expertise needed to implement each attack [2].

Compared to naïve impostor attacks, replay attacks require slightly increased effort; they require recording and replaying. Voice conversion and speech synthesis attacks require specialised, often complex algorithms, in addition to any recording hardware to collect, analyse and parametrise the target and any other auxiliary speech data. They belong to a class of higher-effort spoofing attacks. While voice conversion is based upon the conversion of one speech signal to another, speech synthesis converts a text string to a speech signal, which requires a comparatively higher level of effort or expertise.

One may reasonably suppose that the effectiveness of each attack is correlated with the level of effort involved in their implementation; the higher the effort, the more effective the algorithm and hence the greater the impact on ASV performance. Replay attacks are then assumed to pose only a low threat. However, the work in [13], [36] suggests the contrary, showing that replay attacks pose a significant threat, being effective in overcoming an ASV system while being the most easily implemented spoofing attack. This paper investigates these findings and compares at a high level the threat of replay spoofing to those of speech synthesis and voice conversion.

III. REPLAY COUNTERMEASURES

Attention now turns to the detection of replay spoofing attacks with dedicated countermeasures. Given that only little work has investigated ASV vulnerabilities to such attacks, it is hardly surprising that work to develop countermeasures is similarly limited. This section briefly reviews that past work and then describes two particular replay countermeasures which are explored further in this paper.
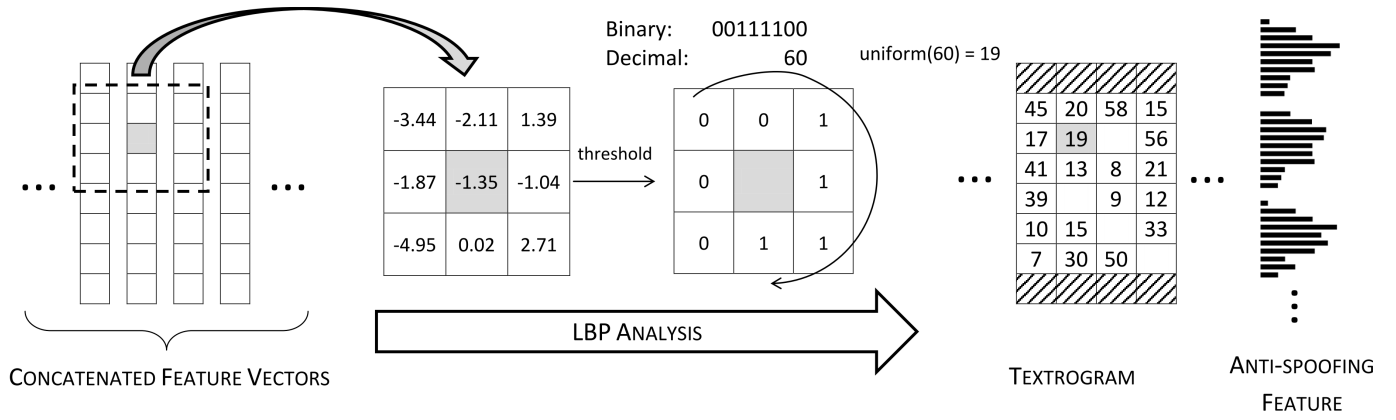
Fig. 2: Schematic diagram of LBP-based feature extraction.

A. General approaches

One obvious approach to replay detection involves challenge-response systems which require the speaker to utter a prompted phrase [37]. Challenge-response mechanisms are a form of passive countermeasure. While having potential in preventing some forms of replay attack for some ASV systems, challenge-response countermeasures are not without impacts on usability which may render them undesirable for other ASV systems. Challenge-response systems also lack sufficient scientific validation.

Active countermeasures have also been proposed. One such approach, based upon the detection of so-called pop noise, is proposed in [38]. Pop noise is a short-duration, typically low-frequency artefact resulting from the impact of natural speech upon a close-talk microphone. Since most loudspeakers exhibit poor fidelity at low frequencies, pop noise is normally attenuated upon replay. The absence of natural pop noise thus serves as an indicator of replay attacks. Two different approaches to measure pop noise are described in [38]. The first, single-channel method is based upon estimates of low-frequency energy, which is characteristic of pop noise. The second, double-channel method, is based upon the difference between two signals captured by two microphones, one of which is equipped with a pop noise filter. Results show that replay attacks can be detected with an EER of as little as 4% where speech is captured using a headset microphone. Performance is, however, greatly reduced in the case of telephony speech; pop noise is in any case attenuated as a result of narrowband transmission.

A different approach involves the storing of previous access attempts and their comparison to new attempts [39]. New access attempts which are deemed too close to previous attempts are rejected. A somewhat similar technique is proposed in [13], where the authors compare spectral bitmaps between access trials and previously stored recordings in a text-dependent ASV scenario.

A alternative method of detecting replay attacks was proposed recently in [40]. It is based on the distances between landmark points in the amplitude spectrum of the speech signal. When assessed in a fixed-phrase scenario with data collected from 175 speakers, a detection EER of 1% was achieved. The detection of high similarity thus serves as an effective means of identifying replay attacks, albeit in somewhat constrained scenarios.

Other, more generally applicable methods, not restricted to a specific ASV scenario, are based on the detection of unexpected channel artefacts indicative of recording and replaying. Two such algorithms are reported in [41] for which the EER for a baseline Gaussian mixture model (GMM) system with a universal background model (UBM) was shown to decrease from 40% to 10% with active countermeasures.

A more recent study [42] describes the application of a deep neural network to detect replayed speech. When assessed on the standard Wall Street Journal (WSJ) corpus [43], adapted to the assessment of replay attack spoofing, a detection EER of 7.5% was achieved. The detection of channel artefacts is also the basis of the first approach investigated further in this paper.

B. Far-field channel detection

Many scenarios in which user authentication is performed by ASV involve so-called close-talk speech, i.e. situations where speech is collected from an in situ or closely positioned microphone. Examples include telephony and logical access scenarios or critical infrastructure protection and physical access scenarios. In contrast, since they are likely to be collected surreptitiously or at-distance, replay recordings may exhibit far-field channel effects, effects which can be measured and consequently used to detect replayed speech.

This idea was first investigated in [44]. The work compares close-talk and far-field speech signals parametrised according to 12 channel-sensitive features:

- spectral ratio – sub-band energy ratio from 0-2 kHz and from 2-4 kHz;
- low frequency ratio – sub-band energy ratio from 100-300 Hz and from 300-500 Hz, calculated using speech frames only;
- modulation index, and
- nine sub-band modulation indices – see [44] for precise sub-band bandwidths.

The spectral ratio reflects the level of spectrum flattening or noise and reverberation introduced by far-field recording.

The low frequency ratio reflects the (potentially heightened) level of high-pass filtering, an artefact typical of speech signals produced by small loudspeakers. The total and sub-band modulation indices reflect the level of additive and, specifically, coloured noise; higher levels of noise present in replay recordings result in lower than average modulation indices. Experiments were performed with a support vector machine (SVM) classifier and showed that far-field recordings could be detected with 90% accuracy.

C. Local binary patterns

The approach to replay detection proposed in [36] is based on the local binary pattern (LBP) analysis of speech spectrograms. Inspired by the original application to image texture analysis [45], the idea was introduced as an ASV spoofing countermeasure in [35]. As illustrated in Fig. 2, LBP analysis is applied to a Mel-scaled cepstrogram with appended dynamic features. Modifications made through spoofing are assumed to disturb the natural 'texture' of genuine speech, attributes which are readily detected with LBP.

The standard LBP operator is a non-parametric 3x3 kernel which assigns a binary code to each pixel in an image according to the comparison of its intensity value to that of its eight surrounding pixels [45]. A binary value of 1 is assigned when the intensity of neighbouring pixels (here feature components) is higher, whereas a value of 0 is assigned when neighbouring pixels are of lower or equal intensity. Each pixel is thus assigned one of $2^8 = 256$ binary patterns. As is common in other applications, e.g. that in face recognition [46], only a subset of the so-called uniform binary patterns are used, i.e., LBPs which contain at most two bitwise transitions from 0 to 1 or 1 to 0 when the bit pattern is traversed in circular fashion.

LBPs can be determined for each pixel in a Mel-scaled cepstrogram thus resulting in a new matrix of reduced dynamic range, here referred to as a *textrogram*. The textrogram captures short-time feature motion beyond that in conventional dynamic parametrisations. Normalised histograms of pixel values constructed for each row of the textrogram are stacked vertically to obtain the anti-spoofing feature vector in the same manner as GMM mean-vectors are stacked to form supervectors. In the work reported here, LBP-based features are calculated for the both the enrolment and test data. The two resulting feature vectors are compared using histogram intersection and the resulting score is thresholded to decide if the test signal is genuine speech or a spoofing attack.

Experimental results presented in [35] showed that the LBP-based textrogram analysis is effective in detecting a range of spoofed speech signals, including artificial signals, speech synthesis (EERs of below 1%) and voice conversion (EER in the order of 7%). The motivation for using LBP analysis as a means of detecting replay attacks is described in Section IV-D.

IV. EXPERIMENTAL SETUP

The comparison of replay, speech synthesis and voice conversion spoofing attacks necessitates controlled experiments with a large, standard corpus, a variety of ASV systems and judicious experimental protocols. They are described here with full details of the wider experimental setup.

A. Methodology

This work aims to compare in a meaningful manner the threat of replay, speech synthesis and voice conversion spoofing attacks. The goal places significant constraints on the choice of dataset, limiting the scope to those for which speech synthesis and voice conversion assessments have already been reported. Large, standard datasets are also preferred.

The work reported here is performed on a subset of the public corpora released in the context of the speaker recognition evaluation (SRE) campaigns administered by the National Institute for Standards and Technology (NIST) [47]. While the use of standard databases enables the comparison of results to others' work, it also necessitates artificial replay emulation. While not ideal, this approach is preferred since it enables the comparison of results for replay, speech synthesis and voice conversion using otherwise identical protocols (and same source data). It is stressed, however, that the work uses impulse responses measured using real playback hardware and real acoustic environments.

B. ASV systems

Since previous work in ASV anti-spoofing has shown different vulnerabilities for different ASV systems, this work is similarly performed with a range of representative technologies, from the standard to the state-of-the-art. They include: (i) a standard Gaussian mixture model with universal background model (GMM-UBM) system [48]; (ii) a GMM supervector linear kernel (GSL) system [49]; (iii) a GSL system with nuisance attribute projection (NAP) [50]; (iv) a GSL system with factor analysis (FA) [51]; (v) a GMM-UBM system with factor analysis; (vi) an iVector system [52] with probabilistic linear discriminant analysis (PLDA) [53] and length normalisation [54] (referred to from here on as IV-PLDA). Experiments were performed with and without score normalisation. Symmetric normalisation (S-norm) [55] was applied to the IV-PLDA system while test normalisation (T-norm) [56] was used for the others. These particular normalisation strategies were chosen since they gave the best results in each case.

All ASV systems are implemented with the same LIA-SpkDet toolkit [57] and the ALIZE library [58] and stem from the work in [51]. They use a common UBM with 1024 Gaussian components and a common feature parametrisation: linear frequency cepstral coefficients (LFCCs), their deltas and delta energy. A speech activity detector is also common to each system. It fits a 3-component GMM to the log-energy distribution and adjusts the speech/non-speech threshold according to the GMM parameters [59]. This approach has been used successfully in many independent studies, e.g. [60].

C. Datasets, protocols and metrics

Experiments are performed on the male subsets of the 2004, 2005, 2006 and 2008 NIST SRE datasets, which are from here on referred to as NIST'0x. The NIST data is

of telephony quality, with a sampling frequency of 8 kHz and μ-law compression. The NIST'04 and NIST'08 datasets are used for UBM training. The NIST'05 dataset is used for development, whereas the NIST'06 dataset is used for evaluation; only results for the latter are reported here. Due to the significant amount of data necessary to estimate the total variability matrix T used with the IV-PLDA system, the NIST'06 dataset is added to the pool of background data for development whereas the NIST'05 dataset was used for evaluation. T is thus learned using approximately 11,000 utterances from 900 speakers, while independence between development and evaluation datasets is always respected.

So as to provide suitable training or adaptation data for speech synthesis and voice conversion spoofing attacks, and for consistency with our previous work, all experiments relate to the 8conv4w-1conv4w condition, where one conversation corresponds to an average of 2.5 minutes of speech (one side of a 5 minute conversation). In all cases, however, only one of the eight, randomly selected training conversations is used for enrolment. Results presented in this paper are thus comparable to those in the literature (not work related to spoofing) for the 1conv4w-1conv4w condition.

Standard NIST protocols dictate 1,352 true client tests and 12,648 impostor tests for development and evaluation datasets. To assess spoofing, impostor tests are replaced with spoofed versions of the original utterance, whereas genuine client trials are unchanged. This approach naturally reduces the number of feasible impostor/spoof trials; whereas zero-effort impostor trials can involve any number of impostors, spoofing attacks are formulated for a single target speaker, namely that whose model is under attack. As a result, while all experiments related to spoofing or countermeasure assessment involve the same true client tests as for the baseline condition, there is a reduced number of approximately 1,000 spoofed trials. Given the constraints, the latter is unavoidable. This setup broadly conforms to the general protocols outlined in [2], [30] and the general evaluation methodology described in [61].

Other, unavoidable differences between the baseline and spoofing protocols relate to the variability in phone content. Voice conversion attacks naturally have the same phone content as the original zero-effort impostor trials. Speech synthesis attacks were generated using arbitrary texts with a similar duration to that of the original zero-effort imposter trial. Replay attacks naturally contain the same phone content as that in another recording of the same, client speaker. Since differences in phone content are perhaps undesirable, the use of relatively long duration trials ensures that they have negligible impact on results; the use of long duration trials ensures that any effect of phone variation is essentially normalised.

Given the consideration of spoofing, and without any standard operating criteria under such a scenario, the EER metric is preferred to the minimum detection cost function (minDCF). Also reported is the spoofing false acceptance rate (SFAR, [62]) for a false rejection rate (FRR) fixed to the baseline EER.

D. Spoofing emulation

Spoofing attacks are generally assumed to be performed at the microphone level. In the case of voice conversion and speech synthesis, the practical scenario would then involve the recording of suitable data for the training or adaptation of conversion or synthesis systems, the fabrication of a spoofed utterance and then its presentation to the microphone of the ASV system. None of the past work (including the authors') follows this process, preferring instead to emulate spoofing attacks by intervening after the microphone, immediately prior to feature extraction. This approach is entirely justified in the case of linear transducers and channels, and mainly telephony scenarios in which spoofing can in any case be applied while bypassing the microphone [63].

Voice conversion spoofing attacks are emulated with the approach described in Section II-B. A worst-case scenario is considered; conversion is performed with full prior knowledge of the ASV system, i.e. voice conversion is performed with exactly the same front-end processing as that used for ASV. $H_y(f)$ and $H_x(f)$ use 19 LPCC and LPC coefficients respectively, with the former being obtained according to Eq. 4 using 1024 Gaussian components. Voice conversion is applied to the original impostor utterances which are converted towards the genuine speaker for any given trial.

Speech synthesis attacks are emulated according to the approach described in Section II-A using an open source voice cloning toolkit[2] which is based on HTS. It uses a default configuration and default, standard speaker-independent models provided with the toolkit. They are trained using American-English speech data from the Effective Multilingual Interaction in Mobile Environments (EMIME) corpus [64]. Adaptation data for each target speaker comprises three utterances (with transcriptions). For any given trial, speech synthesis spoofing attacks are generated using arbitrary text, thereby producing a spoofed utterance of duration close to that of the average test utterance.

Replay attacks are emulated according to the approach described in Section II-C using a random mix of three different loudspeaker impulse responses $\mathrm{spk}(t)$ and three different replay environments $b(t)$. Speaker impulse responses $\mathrm{spk}(t)$ are obtained from [65] and correspond to a low-quality smartphone speaker, a medium-quality tablet speaker and a high-quality stand-alone speaker. The impulse response and frequency responses of each are illustrated in Fig. 3. There are significant differences in the frequency responses which show in particular the high-pass functions of the smaller (and perhaps lower quality) devices. The third impulse response is comparatively flat, though with greater high-frequency attenuation. The first two impulse responses are, however, comparatively short, whereas significant distortion in the third extends to 2ms.

The first two replay environment impulse responses $b(t)$ are obtained from [66] and correspond to an enclosed medium-sized office and an open corridor. The impulse and frequency responses of each are illustrated in Fig. 4. The impulse responses are significantly longer in duration than those of
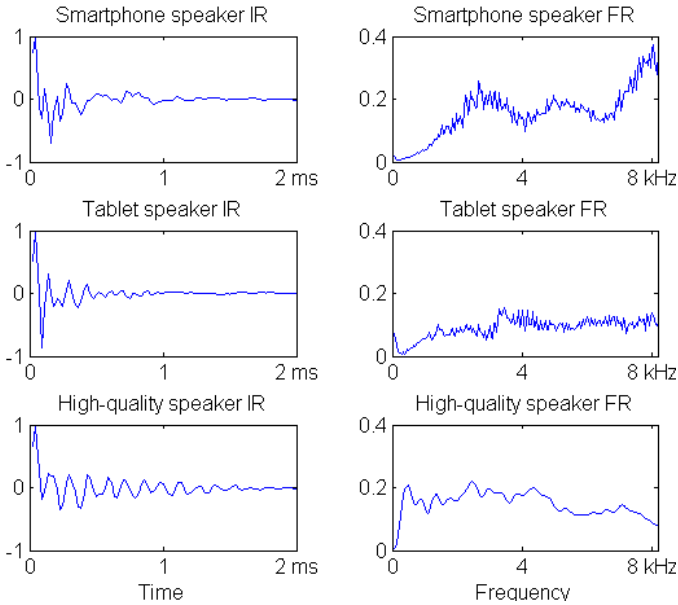
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[2]http://homepages.inf.ed.ac.uk/jyamagis/software/page37/page37.html

Fig. 3: Impulse (left) and frequency (right) responses for three different loudspeakers.

Fig. 4: Impulse (left) and frequency (right) responses for two different acoustic environments.

the loudspeakers, with both extending beyond 500ms. The frequency responses also exhibit far greater fluctuation than those of the loudspeaker responses illustrated in Figure 3. These observations justify the use of alternative features in the exploration of spoofing countermeasures for ASV.

There are two principle motivations for our choice of LBP analysis. First, since an effective spoofing attack must overcome not just any particular countermeasures in place, but also ASV, the most efficient spoofing attacks may be optimised using the same feature representation. Consequently, countermeasures also based upon the same or similar feature representation may not offer the best opportunity for detection. Second, countermeasures essentially aim to detect processing artefacts. Feature diversity is likely to be beneficial. The impulse responses in Figures 3 and 4 show that replay will produce artefacts spanning a duration far in excess of that used typically in the extraction of MFCC features (including dynamic features) and also frequency intervals far smaller. While it is certainly not the only approach, LBP analysis seems well suited to the detection of time-frequency artefacts and is one that has already shown potential in the detection of other spoofing attacks [35], [67].

A third acoustic environment impulse response was also used for the experiments reported in this paper. It is essentially a regular impulse function which simulates an anechoic chamber with a flat frequency response. This particular setup serves to assess the impact of the acoustic environment and its role in the detection of replay spoofing attacks.

It is stressed again that, while this approach to generate spoofing attacks through emulation might seem undesirable at first, it is not without merit. Given representative impulse responses and a time-invariant linear system, then genuine recordings will produce replay attacks that are entirely equivalent to those obtained through emulation. The impact of emulation on the findings of this work is thus negligible.
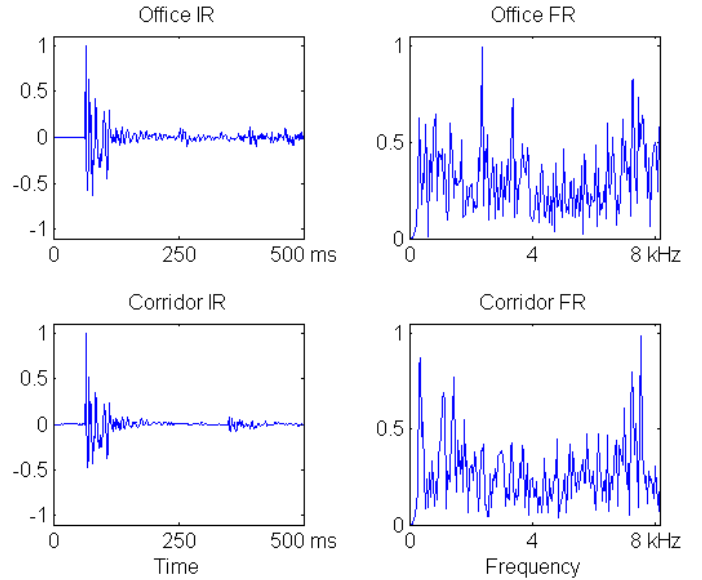
Furthermore, the emulation approach permits a study with many more replay and acoustic environments than would otherwise be practicable with a genuine setup. The emulation approach used here thus has significant merit for this and future work.

E. Countermeasures

The far-field channel detection countermeasure is implemented according to the algorithm originally proposed in [44] and described in Section III-B. The modulation indices are calculated frame-wise from the speech signal envelope which is approximated by the absolute value of the signal after down-sampling to 60 Hz. The final modulation index is calculated by averaging over speech frames whose modulation index is above 0.75.

The LBP countermeasure is implemented using the toolkit provided by The University of Oulu[3]. Normalised acoustic features used for LBP analysis are composed of 51 coefficients: 16 LFCCs and energy plus their corresponding delta and delta-delta coefficients. Analysis is applied only to speech frames and using only the 58 uniform LBPs as originally described in [45] and first investigated for ASV spoofing research in [35]. LBP histograms are created for all but the first and last rows, i.e., for $51 - 2 = 49$ rows. Non-uniform LBPs are ignored thereby resulting in feature vectors of $58 \times 49 = 2842$ dimensions.

Both countermeasure algorithms are trained using a random subset of 1000 utterances from the NIST'05 dataset which are treated as described in Section IV-C in order to generate suitable training data with various acoustic conditions. The use of loudspeaker and acoustic environment impulse responses (a lecture room, a staircase and a meeting room) different to those used for ASV experiments aims to minimise countermeasure over-fitting.

[3]http://www.cse.oulu.fi/CMV/Downloads/LBPMatlab

A Bayesian network classifier [68] is learned to differentiate genuine data from spoofed data in the case of the far-field channel detection countermeasure. This classifier uses a network of probabilistic dependencies between random variables. In contrast, the AdaBoost M1 meta classifier [69] is used for the LBP countermeasure. This classifier uses other 'weak' classifiers, in this case decision trees, and iteratively boosts their performance by exposing them to previously misclassified instances. These two classifiers, both implemented using the Weka toolkit [70], returned the best results in each case for an area-under-the-ROC metric.

Reported later are baseline ASV results, ASV results when subject to spoofing and then results for the same system with integrated countermeasures. Countermeasures are also assessed independently from ASV systems as per the protocol described in Section IV-C. This is similar in characteristic to that used in related work, e.g. the ASVspoof 2015 evaluation [30] (which does not include replay attacks). There are then 1,352 genuine trials and 1,352 spoofed trials. These experiments are repeated individually for the nine different replay conditions involving different loudspeakers and acoustic environments, leading to an overall number of 12,168 spoofing trials.

Countermeasures are integrated with ASV as described in [35], once again following the modified NIST protocol described in IV-C. In this case, the countermeasure threshold is set heuristically to minimise the EER of the ASV system. Trials classified as spoofs are assigned an arbitrarily low score and are thereby rejected automatically.

V. RESULTS

Attention now turns to the assessment of ASV vulnerabilities. With a strictly controlled protocol, the potential impact of replay attacks is compared to that of speech synthesis and voice conversion. It is stressed that the experiments do not and cannot evaluate every possible replay scenario in exhaustive fashion. It is neither possible to evaluate speech synthesis, voice conversion and replay in every possible use case scenario. The aim is to gauge at a high level the relative threat in order to prioritise future work, i.e. to determine whether or not replay attacks warrant greater attention than they have in the past. Beyond this, the aim is also to determine the potential and difficulty to detect replay attacks with dedicated countermeasures.

A. Replay spoofing

Fig. 5 shows the effect of replay attacks on the score distributions for the IV-PLDA system. Replay attacks correspond to an emulated high-quality speaker and office environment. Three distributions are illustrated: (i) the zero-effort impostor distribution; (ii) the genuine client distribution, and (iii) the distribution obtained when all zero-effort impostor trials are replaced with replay attacks. While the zero-effort impostor and genuine client distributions are well separated, the latter overlaps significantly with the score distribution for replay attacks. Increased overlap between these distribution will degrade ASV performance.
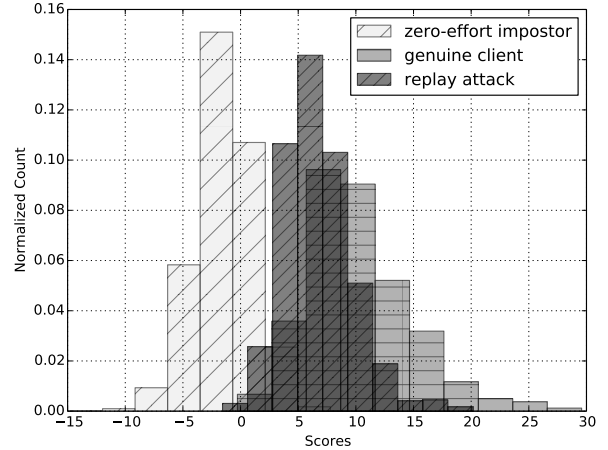

Fig. 5: Score distribution for the IV-PLDA system for replay attacks using an emulated high-quality speaker and an office environment.

Fig. 6 illustrates a detection error trade-off (DET) plot[4] for the same experimental setup. The lower-most, solid profile illustrates the performance of the baseline ASV system and shows a competitive EER of below 3%. The upper-most, dashed profile illustrates performance when zero-effort impostors are replaced with replay attacks. The difference between these two profiles thus serves as an indication of system vulnerability to replay spoofing; in this case the degradation in performance is significant.

This trend is observed across the full set of six ASV systems and nine different replay attack configurations; these results are summarised in Table II. Results in the second row show the baseline performance for each ASV system and for only zero-effort impostors. As expected, the IV-PLDA system delivers the lowest EER. Rows 3–5 illustrate the degradation in performance when zero-effort impostors are replaced with replay attacks applied in three different acoustic environments.

EERs in Table II are averaged across the three loudspeaker configurations; other results not reported here showed greater sensitivity to the acoustic environment than to the loudspeaker characteristics. These observations are discussed in greater detail below. The performance of all six systems degrades significantly. The EER of the most sensitive GSL system increases from 8% to in the order of 90% for all three acoustic environments. This degradation is currently attributed to the effect of T-norm, however this hypothesis requires further investigation. Even the EER of the most resistant GSL-FA system increases to between 22% and 50%. Finally, the EER of the state-of-the-art IV-PLDA system increases to between 25% and 50%.

B. Comparison to voice conversion and speech synthesis

DET profiles showing the comparative vulnerabilities to replay, voice conversion and speech synthesis attacks are

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[4]The DET plots were produced with the TABULA RASA Scoretoolkit (http://publications.idiap.ch/downloads/reports/2012/Anjos_Idiap-Com-02-2012.pdf).

	GMM	GSL	GSL-NAP	GSL-FA	FA	IV-PLDA
Baseline	8.63	8.13	6.31	5.72	5.61	2.98
Replay: office environment	60.32	92.98	29.92	28.54	30.12	30.30
Replay: corridor environment	55.91	88.20	23.59	21.62	24.97	24.53
Replay: anechoic environment	64.40	96.67	49.44	49.31	49.67	49.46
Voice conversion	33.69	36.92	27.58	23.97	23.96	19.30
Speech synthesis	27.29	15.04	13.78	11.91	16.22	10.82

TABLE II: Equal error rates (EERs) for six different ASV systems and for zero-effort impostors (baseline) and three different replay acoustic environments for which results are averaged across the three different loudspeaker configurations. (Note that, while EERs in excess of 50% could be reduced by reversing the hypothesis decision, this would render the system entirely vulnerable to naïve impostor attacks.)
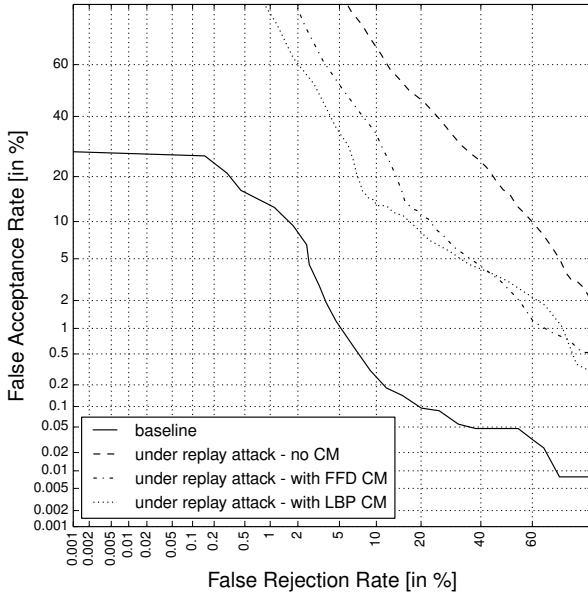

Fig. 6: DET plots for the IV-PLDA system: (i) the baseline, (ii) under replay spoofing with a high-quality speaker in an office, (iii) under replay attack, but with FFD and (iv) LBP countermeasures.
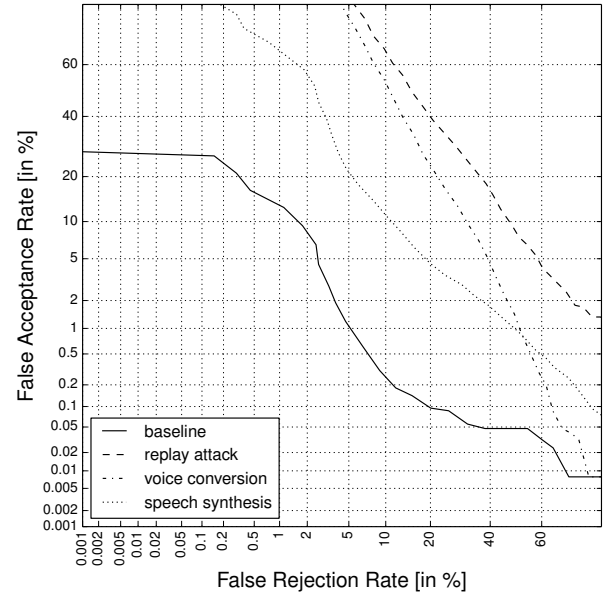

Fig. 7: DET plots for iVector-PLDA system and various attacks.

illustrated in Fig. 7 for the IV-PLDA system. Recalling the aim of the work to compare at a high level the relative threat of replay attacks to those of speech synthesis and voice conversion, the comparison of such profiles is not intended to be strictly meaningful[5] they are sufficient to show that it is a mistake to discount the threat of replay attacks. This trend is consistent across the full range of ASV systems.

Tab. II show degradations in performance when the full range of ASV systems are instead tested with speech synthesis and voice conversion spoofing attacks instead of replay. Again, while the comparisons are not strictly meaningful, they show that replay attacks pose at least a comparative threat. A better balanced consideration of replay attacks is clearly needed in the future.

[5]Different spoofing algorithms will yield different degradations in ASV performance. For example, other authors [27], [29], [30], show greater vulnerabilities for speech synthesis.

C. Replay countermeasure

Fig. 8 illustrates (independently of ASV) the performance of the far-field (FFD) and local binary pattern (LBP) countermeasures in detecting replay attacks. Results are illustrated for attacks emulated using a high-quality loudspeaker and averaged across both office and corridor environments. Results show that the LBP countermeasure yields better results than the FFD countermeasure (EERs of 2.87% and 16.53% respectively). Since no far-field effects were included in the replay emulation, the comparison is in any case biased in favour of the LBP countermeasure. The step-like nature of the DET curve for the LBP countermeasure is typical in the case of classifiers based on decision trees, such as the AdaBoost M1 classifier used in this work.

The middle two profiles in Fig. 6 show the impact of each countermeasure when integrated with the IV-PLDA ASV system. While both countermeasures show reductions in the EER compared to the upper-most profile, performance still remains far from the baseline.

Environment	EER (%)			SFAR (%)		
	no CM	with FFD	with LBP	no CM	with FFD	with LBP
Office	30.30	13.62	9.56	88.70	63.93	46.29
Corridor	24.53	11.34	7.00	80.91	50.25	30.52
None	49.46	42.14	46.77	97.00	95.17	95.76

TABLE III: EER and SFAR values for various environment of replay attacks, with and without the FFD or LBP countermeasures applied, for IV-PLDA. The SFAR was measured for FRR equal to the baseline EER (2.98%).
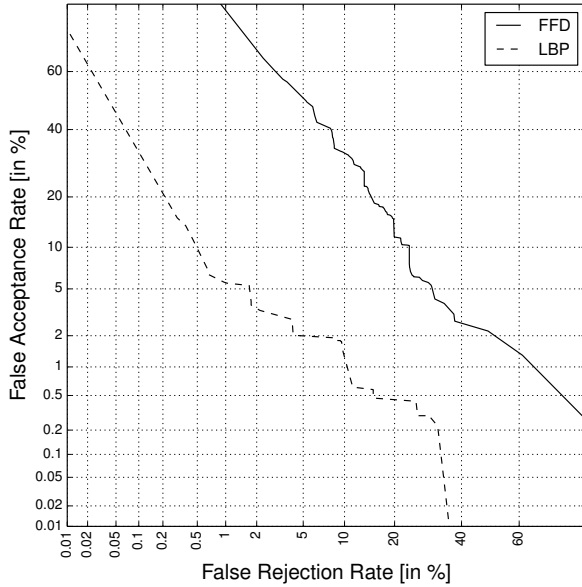

Fig. 8: DET plots for replay spoofing detection using the FFD or LBP countermeasures (assessment independent from ASV), for a high-quality loudspeaker.

Detailed results for FFD and LBP countermeasures and three replay environments are presented in Table III. Results are again averaged for the three different loudspeakers and are presented in terms of both EER and SFAR [62]. Consistent with results in Fig. 6, the LBP countermeasure again outperforms the FFD countermeasure. While replay in office and corridor environments leads to significant degradations in ASV performance, EERs with active countermeasures are less than 10%. Even so, they remain high. Even if the reduction in equivalent SFAR results is significant, and even with active countermeasures, the SFAR remains no lower than 30%. These results suggest that replay spoofing is far from a solved problem.

Unsurprisingly, results for the anechoic environment show that neither countermeasure performs well. This result shows that the loudspeaker effects are not sufficient on their own in order to detect replay. They show that both countermeasures are essentially relying upon the detection of the acoustic environment. These observations point towards ideas for future work described in Section VI.

D. Interpretation of results

The results presented above corroborate the findings of previous work performed with considerably smaller databases; unsurprisingly, replay attacks represent a tangible threat to the reliability of ASV systems. While reporting the first work with NIST databases and replay attacks emulated in similar fashion to past work with speech synthesis and voice conversion, some aspects of this work must be highlighted in order that results are sensibly and fairly interpreted.

First, the results show that replay attacks represent a threat which is comparable to those of speech synthesis and voice conversion; they are not intended, nor sufficient to show that replay attacks cause a greater degradation in ASV performance. The relative degradations are naturally a function of the authors' effort and expertise in each approach. Other, perhaps more sophisticated speech synthesis and voice conversion algorithms may well cause greater degradations in ASV performance than those reported here. Furthermore, in some sense it is in any case impossible to compare threats on a fully level playing field. Significant application factors, for instance, could not been taken into account in this work. Results should therefore be interpreted only as evidence that the threat of replay to ASV robustness merits greater attention in the future.

These arguments lead naturally to the comparisons regarding the effort and expertise involved in the implementation of each spoofing attack. Whereas voice conversion and speech synthesis are relatively high-effort, high-technology attacks, replay spoofing is implemented easily, with no specific expertise nor sophisticated equipment. Accordingly, the threat posed by replay attacks should be considered greater in a practical perspective, even in the case that future work shows degradations in ASV performance cased by replay are lower than those caused by speech synthesis and voice conversion; they are in any case a significant threat and the most likely form of spoofing 'in the wild'.

VI. FUTURE WORK

Some aspects of the results require further work to investigate and explain. Of particular note is the vulnerability of the GSL system whose EER increases to 90% when subjected to replay attacks; all other ASV systems have EERs in the order of 25% to 50%. Our initial investigations have shown that score normalisation may be the cause. Other experiments without score normalisation showed EERs of between 30% and 50%. Accordingly, further work is required to study the impact of score normalisation on ASV vulnerabilities to spoofing.

There are also some as-yet-unanswered questions regarding the impact of channel compensation. The main idea behind the detection of replay attacks essentially involves the detection of unexpected channel effects. Thus, while channel compensation has unquestionable utility in ensuring the usability of ASV across different devices, it may also work to the advantage of the fraudster; it can make the very channel characteristics captured by replay countermeasures more difficult to detect. Further work should investigate this relationship.

The generalisation of the proposed LBP-based countermeasure to different spoofing attacks is another open issue. While this work shows the potential of LBP analysis for replay detection and other, past work has demonstrated its utility for the detection of other spoofing attacks [35], [67], these findings conflict with other researchers' results [71] published after the completion of this work. There are many possible explanations for these contrasting findings and all of these will require further work to investigate properly. Nevertheless, LBP-based countermeasures differ fundamentally from the features used in typical ASV systems and they are adept for the capture of time-frequency artefacts indicative of manipulated speech signals. As such, LBP is an appealing solution to spoofing detection.

The negative results for the anechoic chamber acoustic environment show that neither the FFD not the LBP based countermeasures are unsuccessful in detecting loudspeaker distortion. Performance is thus dependent on the presence of more significant distortion introduced by a non-anechoic acoustic environment. These observations suggest that a solution better tailored to the detection of loudspeaker distortion may be needed and the audio forensics literature may provide suitable tools and algorithms with which to pursue such work.

Finally, further work should assess the threat with a more application-driven methodology. That chosen here was motivated by the need to compare the threat of replay to that of voice conversion and speech synthesis, simply as a means of gauging the threat and for prioritising future work. While the NIST SRE datasets were essential in order to support comparisons to other work, and are almost a requirement as regards publication, they were designed more for surveillance and security scenarios rather than authentication applications more relevant to spoofing. Since replay spoofing is undeniably application specific, future work should thus consider more the application than the dataset. It is stressed, however, that this criticism can be levelled equally to all of the past work, including that in speech synthesis and voice conversion spoofing. The AVspoof database [29], collected and released some time after the work reported here was performed, is one excellent resource to explore ASV spoofing and anti-spoofing with data much better matched to authentication scenarios. This work also shows that the threat of replay attacks should not be ignored.

VII. Conclusions

This paper assesses the threat to automatic speaker verification of replay spoofing attacks. The threat is shown to be of at least similar significance to that of speech synthesis and voice conversion. The latter have attracted by far the greatest attention in the literature to date whereas replay spoofing is under-researched. This paper argues that replay spoofing merits far greater attention; in contrast to speech synthesis and voice conversion attacks, replay attacks require no specialist expertise nor sophisticated equipment and are therefore the most likely attack in practice.

While there is potential to detect replay spoofing attacks, the approaches assessed in this paper rely upon the presence of measurable distortion caused by the acoustic environment. Approaches to channel compensation, universally popular in today's state-of-the-art speaker verification systems, can reduce channel effects thereby increasing the difficulty in detecting replay attacks. In addition, replay attacks recorded with high-quality sound systems may be considerably more difficult to detect. Alternative countermeasures will then be needed. Challenge-response mechanisms are a suitable candidate but lack scientific and objective validation.

Lastly, the practical use of these and any other replay countermeasure are fundamentally dependent on the application. It is extremely difficult to assess replay spoofing, hence some rather bold assumptions in this work and the use of replay emulation. Further work will be needed to assess replay, and spoofing in general, with an application-driven methodology. Whatever the methodology, however, since any security system is only as strong as its weakest link, countermeasures to thwart replay spoofing merit far greater attention than they have in the past.

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