Privacy-preserving iVector based Speaker Verification

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***Abstract*—This paper proposes an efficient algorithm to perform a privacy-preserving speaker verification based on the iVector and linear discriminant analysis. In this research we have considered a scenario in which the users enrol their voice biometric with the third-party service providers to access the different services (i.e., banking). Once the enrolment is completed, the users can verify themselves to the system using their voice instead of passwords. Since the voice is unique for everyone, storing the extracted voice features of the user at the third-party server raises several privacy concerns. To address this challenge, this paper proposes a novel technique based on randomisation to perform voice authentication, which allows the user to enrol and verify their voice in the randomised domain. To achieve this, the iVector based speaker verification technique has been redesigned to work on the randomised domain. The proposed algorithm is validated using the TIMIT dataset. In addition, the proposed algorithm does not compromise the accuracy due to the randomisation as the additional complexity due to the randomisation is negligible.**

***Index Terms*—Privacy, security, speech, iVector, authentication, random domain.**

I. Introduction

TRADITIONAL authentication methods such as passwords, PINs, and memorable words can be easily forgotten, lost, guessed, stolen, or shared. However, authentication using anatomical traits such as fingerprint, face, palm print, iris and voice are very difficult to forge since they are physically linked to the user. Thus, biometric systems impart higher levels of security and have seen a rapid proliferation in a wide variety of government and commercial applications around the world in the last two decades [2]. However, various security and privacy challenges deter the public confidence in adopting biometric based authentication systems. There are several security and privacy challenges that exist in such systems as described below:

Non-revocability: :It is impossible to reverse the biometric data once its compromised; hence, once lost the same values cannot be reused. In case if a person's fingerprint data is compromised then she or he may need to re-enrol using different fingers. If the stolen biometric data characterises voice then it is not wiser for that person to use voice-based authentication for different service providers. In addition it is also possible for someone (adversary) to record an individual's voice and launch an impersonation attack. The impact of this type of attack is minimal compared to an attack on the server containing individual's biometric data. In order to overcome this vulnerability one of the main aims of this paper is to protect the biometric data that is stored in the third party untrusted server.

Privacy compromise: Inappropriate use of biometric data may breach the user's privacy directly and indirectly. The privacy breaches can be categorised into three types as below:

- *Biometric data privacy compromise:* The raw biometric data of the user can be recovered from the stored templates if there are no protections. For example, many fingerprint-based systems use minutiae features and store minutiae extracted from a reference fingerprint image as templates. It is possible to reconstruct the original fingerprint image from the stored minutiae.
- *Information privacy compromise:* When someone enrols their biometric data in different services with the same biometric trait, their biometric templates in all of these systems are identical. This will allow, templates from one system to be used to gain access to another system whereby the user is not authorised to access.
- *Identity privacy compromise:* Since the biometric templates used for different services are reasonably similar, there is a possibility for linkability based attacks.

In the literature (see Section II), there are a number of cryptographic techniques that have been proposed to modify various biometric verification algorithms designed for different biometrics data to mitigate the above problems. To the best of our knowledge, this is the first privacy-preserving work that redesigns the state-of-the-art iVector based speaker verification technique [1] without compromising the accuracy for a negligible computational overhead. The proposed scheme has been validated using the well known TIMIT speech corpus [6]. Theoretical proofs have been provided to validate the privacy and security of the system. Rigorous experiments show that the scheme mitigates the above issues without compromising the accuracy.

The rest of this paper is organised as follows: The related work is discussed in Section II. The speaker verification model without privacy restriction, mathematical tools and notations necessary for the proposed algorithm are given in Section III. In Section IV, we redesign the iVector based speaker

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verification model using randomisation technique and the associated performance results are given in Section V. The security and privacy analysis is given in Section VI followed by conclusions are discussions.

II. Related Works

The speaker verification over the Internet is becoming very popular after banks and other prominent industries are adopting speaker verification as a mean to verify its customers. At the same time, recent changes in privacy legislation i.e., GDPR in Europe, are enforcing organisations to provide sufficient privacy guarantee when they use, process and store customer data. Since voice data is unique, the privacy of the voice data should be guaranteed.

This requires a novel speaker verification solution with high accuracy and privacy guarantee. Privacy-preserving research address this challenge by balancing privacy and usability of data. When it comes to a privacy-preserving solution, it is all about transforming the existing algorithm to process the inputs when the inputs are either encrypted via homomorphic encryption [3], [5], [7]–[10] or transformed via salting [11], [17].

The ultimate goal of homomorphic encryption based privacy-preserving solutions is protecting the privacy of the input data. However, each of these works redesign different machine learning algorithms i.e., face recognition based on the principal component analysis in [7], facial expression recognition based on the linear discriminant analysis in [10], multi-class problem based on support vector machine in [5], [9], are the few to mention here. The existing homomorphic encryption-based privacy-preserving solutions achieve the same accuracy as their corresponding traditional algorithms subject to hefty computational overhead – in some cases the time required to perform the necessary operations is around minutes [3], [10]. On the other hand, salting based cancellable biometric solutions increase the computation speed significantly compared to the homomorphic encryption-based solutions [11], [17]. However, these solutions either decrease the accuracy or privacy.

There are only a few notable works exist in the domain of privacy-preserving speaker verification that we can use to benchmark our solution [3], [11], [14], [16], [17]. In [14], Smaragdis and Shashanka proposed the first application of secure multi-party computation (SMC) concepts for privacy-constrained speech technology. In their work, they realised secure speech recognition using the hidden Markov model (HMM) and a generalised version of the Paillier public-key scheme, which allowed training and classification between multiple parties and achieved perfect accuracy.

Pathak et. al redesigned the Gaussian Mixture Model (GMM) based speaker recognition [3] to achieve a similar privacy goal. The work in [3] relies on homomorphic cryptosystems such as BGN and Paillier encryption. This work has shown a proof-of-concept of privacy-preserving speaker recognition without compromising the accuracy. However, the shortcoming of these cryptographic approaches [3], [14] is that far too much time is spent on the encryption, which makes it impractical for real-life applications i.e., [3] requires few minutes for authentication.

In order to overcome the heavy computation that is involved with the homomorphic encryption schemes [3], [14], string-matching frameworks were proposed in [11], [17]. The schemes in [11], [17] proposed to convert the speech input represented by the super-vectors to bit strings using locality sensitive hashing (LSH) and counted the exact matches. Since it is easy to perform string comparison with privacy, the method proves to be more efficient; however, it lacks accuracy with EER=11.86%.

To the best of our knowledge, one and only work that proposes a privacy-preserving solution for ivector based speaker verification is [16]. The work in [16] presented a secure binary embedding (SBE) which is a hashing scheme in an attempt to use the iVector based speaker recognition to support privacy. The work in [16] used a hashing technique where similar templates are placed in close proximity in the hash domain. The inherent nature of hashing, the verification accuracy obtained in [16] is much lower than the true accuracy (when the traditional ivector solution provides EER = 1%, their proposed privacy-preserving solution provides EER = 20% [16] when the privacy is high).

In contrast to all the above works, the proposed work uses randomisation technique from information theory which is neither computationally inefficient nor compromises the privacy. Our work not only provides the speed necessary for real-time computation but also provide information-theoretical privacy and highest possible accuracy. This solution is significantly advanced than the existing solution in terms of accuracy, privacy and speed. Note that the proposed solution can be applied to variants of ivector based speaker verification solutions that calculates scores using cosine distances. If a solution such as PLDA based ivector [19] uses different scoring method then the proposed solution may not be sufficient.

III. Speaker recognition based on iVector and Cosine Distance Scoring

Recently Dehak et. al [1] proposed a pioneering work, namely *iVector*, for speaker verification. The iVector model generates a low-dimensional speaker-and-channel dependent space using factor analysis. Serveral channel compensation techniques such as, within-class covariance normalisation, linear discriminant analysis, and nuisance attribute projection, were applied in [1] on this low dimensional space to remove the channel dependent noise. Through rigorous experiments, the work in [1] concluded that iVector and linear discriminant based speaker verification outperforms the other competitive techniques and became one of the state-of- the-art speaker verification techniques.

Hence, as discussed in Section I, a privacy-preserving version of ivector based speaker verification model is developed in this paper. The objective of this work is to achieve privacy within user-server settings without reducing the accuracy at a negligible complexity overhead. The following section briefly describes the speaker verification model proposed in [1].

The work proposed in [1] mainly constitutes of two parts: 1) iVector feature extraction and speaker model building and

2) speaker verification. The first part extracts features of speech using several techniques such as Mel frequency cepstral coefficients (MFCC), Gaussian Mixture Model (GMM), Universal Back ground model (UBM), and maximum a posterior adaptation (MAP) [4] followed by speaker model building i.e., obtaining matrix $\mathbf{R}$ in the equation (2) below. Once $\mathbf{R}$ is obtained, voice feature of a user, called ivector, $\mathbf{w}_{\text{target}}$, can be enrolled in the server. For additional technical details of the first part, the readers are referred to [1].

During the second part (i.e., speaker verification), the user is required to send voice feature vector $\mathbf{w}_{\text{test}}$ to the server. The authors in [1] use cosine distance scoring for speaker verification. The cosine distance scoring computes the value of the cosine kernel between the target speaker i-vector $\mathbf{w}_{\text{target}} \in \mathbb{R}^{d\times 1}$ and the test i-vector $\mathbf{w}_{\text{test}} \in \mathbb{R}^{d\times 1}$ as a decision score [1]

$$\text{score}(\mathbf{w}_{\text{target}}, \mathbf{w}_{\text{test}}) = \frac{< \mathbf{w}_{\text{target}}, \mathbf{w}_{\text{test}} >}{||\mathbf{w}_{\text{target}}||||\mathbf{w}_{\text{test}}||} \gtreqless \theta, \quad (1)$$

where dimension d is the size of the iVector (i.e., $d = 200$ in the experiments in Section V-D). In order to compensate the channel effect, authors in [1] considered three different channel compensation techniques namely 1) within-class covariance normalisation (WCCN), 2) linear discriminant analysis (LDA), and 3) nuisance attribute projection (NAP). All three techniques above compute projection matrices $\mathbf{P}_{\text{WCCN}}$, $\mathbf{P}_{\text{LDA}}$, and $\mathbf{P}_{\text{NAP}}$ from training speech data. In the following the projection matrices are denoted by $\mathbf{P}$ (i.e., $\mathbf{P} \equiv \mathbf{P}_{\text{WCCN}} \equiv \mathbf{P}_{\text{LDA}} \equiv \mathbf{P}_{\text{NAP}}$).

In order to preserve the inner-product in (1), and to apply these channel compensation techniques, Dehak et. al [1] used the following approach

$$\begin{aligned} & \text{score}(\mathbf{w}_{\text{target}}, \mathbf{w}_{\text{test}}) \\ = & \frac{(\mathbf{P}^T\mathbf{w}_{\text{target}})^T(\mathbf{P}^T\mathbf{w}_{\text{test}})}{\sqrt{(\mathbf{P}^T\mathbf{w}_{\text{target}})^T(\mathbf{P}^T\mathbf{w}_{\text{target}})}\sqrt{(\mathbf{P}^T\mathbf{w}_{\text{test}})^T(\mathbf{P}^T\mathbf{w}_{\text{test}})}}, \\ = & \frac{\mathbf{w}_{\text{target}}^T\mathbf{R}\mathbf{w}_{\text{test}}}{\sqrt{\mathbf{w}_{\text{target}}^T\mathbf{R}\mathbf{w}_{\text{target}}}\sqrt{\mathbf{w}_{\text{test}}^T\mathbf{R}\mathbf{w}_{\text{test}}}} \gtreqless \theta \end{aligned} \quad (2)$$

where $\mathbf{R} = \mathbf{P}\mathbf{P}^T \in \mathbb{R}^{d\times d}$.

If we consider a traditional speaker recognition system (i.e., without privacy constraints), during the enrolment phase, the user device extracts a feature vector $\mathbf{w}_1$ from a speech utterance and send it to server. The server obtains $\mathbf{R}$ from all the users who uses the system for speaker verification. During the recognition phase, the user device extracts another feature vector $\mathbf{w}_2$ from a speech utterance and send it to the server. Now the server computes the score using the feature vectors $\mathbf{w}_1$ and $\mathbf{w}_2$ and matrix $\mathbf{R}$ as follows:

$$\text{score}(\mathbf{w}_1, \mathbf{w}_2) = \frac{\mathbf{w}_1^T\mathbf{R}\mathbf{w}_2}{\sqrt{\mathbf{w}_1^T\mathbf{R}\mathbf{w}_1}\sqrt{\mathbf{w}_2^T\mathbf{R}\mathbf{w}_2}}. \quad (3)$$

If $\text{score}(\mathbf{w}_1, \mathbf{w}_2) > \theta$ then the server will assume that the feature vectors $\mathbf{w}_1$ and $\mathbf{w}_2$ are generated by the same user.

IV. Model, Overview and Privacy-preserving approach

Consider a scenario where N number of users registered with a service provider using their voice biometric. Lets refer to the voice template enrolled in the server $\mathbf{w}_1$ as the *speaker model*. Once the enrolment is completed, the server authenticates the user using user's voice. To be authenticated, the user needs to send a voice template $\mathbf{w}_2$ to the server - refer this template as the *test feature*. The server verifies the test feature against the speaker model.

Since this paper proposes a privacy-preserving model, lets introduce a *secret key* (refer Section IV-B for more details) to randomise (i.e., similar to encryption) speaker model and test feature. Once the speaker model and test feature are randomised (refer them as *randomised speaker model* and *randomised test feature*), the secret key is split into two shared-secret-keys (one for user and one for server).

Since there are N users, the server holds N randomised speaker models and N shared secret keys. During the authentication stage, the user device captures user's speech and generates a test feature vector. Then the user device randomises the test feature vector using it's shared secret key and send the randomised test feature to the server. Within this context, lets define the following privacy threats and goals of the proposed work.

Revocablity: If the randomised speaker model at the server is compromised by an adversary, it should be possible the revoke the randomised speaker model and enrol new randomised speaker model.

Template diversity: If an adversary has access to the randomised speaker models registered at different service providers, then it should be infeasible for that adversary to reveal whether the same user has been registered for different services.

Compromising the test feature: If an adversary has access to the the test feature used during the authentication stage, then it should be infeasible for the adversary to impersonate the user in future.

Compromising the data from the user device: If the secret key is compromised by the adversary from the user's device then the adversary cannot use that key to impersonate the user in future.

In order to address the above privacy threats, the traditional speaker verification needs to be redesigned. Lets introduce a cryptographic primitive called *randomisation technique* in the following section to develop a privacy-preserving speaker verification.

A. Randomisation technique

Denote an integer message $m \in \mathsf{M} = \{-2^M \text{ to } 2^M\}$ and an integer secret key $s \in \mathsf{S} = \{-2^R - 2^M \text{ to } 2^R + 2^M\}$ where M and R are integers and $2^R >> 2^M$. Lets assume that the secret key $s \in \mathsf{S}$ is generated randomly from a uniform distribution in the range of $\mathsf{S} = \{-2^R - 2^M \text{ to } 2^R + 2^M\}$. Now the following algorithm can be used to randomise the message m into a randomised message $r \in \mathsf{R} = \{-2^R \text{ to } 2^R\}$ using s.

Lets consider a toy example with a message domain $\mathsf{M} = \{-2 \text{ to } 2\}$ (i.e., $M = 1$), randomised message domain $\mathsf{R} = \{-4 \text{ to } 4\}$ (i.e., $R = 2$) and secret key domain $\mathsf{S} = \{-6 \text{ to } 6\}$ ($M = 1$ and $R = 2$) to understand the

Algorithm 1 Randomisation Technique

```
1: procedure RANDOMISE(m)
2:     Generate secret key s
3:     DO r = m + s
4:     IF r ∈ {−10^R to 10^R}
5:         Return r, s
6:     ElseIF
7:         Go to Step 2
8:     EndIF
```

Table I
RANDOMISATION: A TOY EXAMPLE.

Randomised Messages [-4 to 4] (i.e., $R=2$)	Possible Messages [-2 to 2] (i.e., $M=1$)	Possible Secret Key Values [-6 to 6] (i.e., $M=1$ and $R=2$)
-4	-2, -1, 0, 1, 2	-2, -3, -4, -5, -6
-3	-2, -1, 0, 1, 2	-1, -2, -3, -4, -5
-2	-2, -1, 0, 1, 2	0, -1, -2, -3, -4
-1	-2, -1, 0, 1, 2	1, 0, -1, -2, -3
0	-2, -1, 0, 1, 2	2, 1, 0, -1, -2
1	-2, -1, 0, 1, 2	3, 2, 1, 0, -1
2	-2, -1, 0, 1, 2	4, 3, 2, 1, 0
3	-2, -1, 0, 1, 2	5, 4, 3, 2, 1
4	-2, -1, 0, 1, 2	6, 5, 4, 3, 2

above randomisation technique. The possible messages, secret keys and the corresponding randomised messages for the toy example are shown in Table I.

Let's suppose the randomised message is -4. This -4 could have been obtained from any messages in the message domain (i.e., -4 = -2 + -2 or = -1 + -3 or = 0 + -4 or = 1 + -5 or = 2 + -6). Similarly if the randomised message is -3, this randomised message could have been obtained from any possible messages (i.e., -3 = -2 + -1 or = -1 + -2 or = 0 + -3 or = 1 + -4 or = 2 + -5). It is obvious from Table I any randomised message could be generated from any message. Hence, if an attacker compromises a randomised message then it is impossible for the adversary to recover message m from the randomised message r without knowing the secret key s i.e., *posterior probability* and *prior probability* of the messages are equal. Hence this algorithm follows information-theoretic security [13] (refer Section VI for formal proof).

B. The Proposed Privacy-preserving approach

The previous section described the mathematical model for state-of-the-art speaker recognition without any privacy requirements. This section proposes two algorithms namely 1) basic approach and 2) strong approach. The basic approach protects the speaker model $\mathbf{w}_1$ residing at the server side and the strong approach protects both the speaker model and test feature vector, $\mathbf{w}_1$ and $\mathbf{w}_2$. The following sections explain both the approaches in detail.

C. The Basic Approach

The basic approach (BA) transforms the speaker model $\mathbf{w}_1$ into a different vector using a one-way cryptographic function such that the transformed version leak nothing about the original values of $\mathbf{w}_1$ albeit it can still be used for speaker recognition. This approach protects against any unwanted privacy leakages if the server happens to be compromised. The randomisation technique proposed in Algorithm 1 can be used as a one-way cryptographic function.

The user uses Algorithm 1 to randomise the feature vector $\mathbf{w}_1$ using a random vector $\mathbf{r}_1$. Then user enrols $\mathbf{w}_1+\mathbf{r}_1$ at the server and keeps $\mathbf{r}_1$. During the recognition phase, the user sends not only the feature vector $\mathbf{w}_2$ but also $\mathbf{r}_1$ to the server. The server first obtains $\mathbf{w}_1$ by subtracting $\mathbf{r}_1$ from the stored randomised feature $\mathbf{w}_1+\mathbf{r}_1$ followed by executing (3). Once the recognition process is completed, the server will keep only the randomised vector $\mathbf{w}_1+\mathbf{r}_1$ and delete all other parameters (i.e., $\mathbf{r}_1$, $\mathbf{w}_2$ and $\mathbf{w}_1$).

Since the speaker model is randomised in the BA approach, any attack on the server will not reveal $\mathbf{w}_1$ to the adversaries. In the event of an attack, the speaker model can be revoked and a new speaker model can be generated. Note that this approach cannot protect the privacy of user biometric if the server has already been compromised by a malware which can monitor the speaker verification process. Hence, the BA approach trusts the server and assumes that the server follows the procedure and free from malware.

D. The Strong Approach

The strong approach (SA) does not require a trusted server for speaker recognition. The objective of the SA approach is that even if the speaker verification server is being compromised by a malware, it should be infeasible for the malware to obtain $\mathbf{w}_1$ and $\mathbf{w}_2$. To achieve this objective, during the enrolment phase, the user randomises the feature vector $\mathbf{w}_1$ using random vectors $\mathbf{r}_1$ and $\mathbf{r}_x$ and enrols $\mathbf{w}_1+\mathbf{r}_1$ and $\mathbf{w}_1^x=\mathbf{w}_1+\mathbf{r}_x$ at the server and keeps $\mathbf{r}_1$ and $\mathbf{w}_1^y=-\mathbf{r}_1$ where

$$\mathbf{w}_1=\mathbf{w}_1^x+\mathbf{w}_1^y. \tag{4}$$

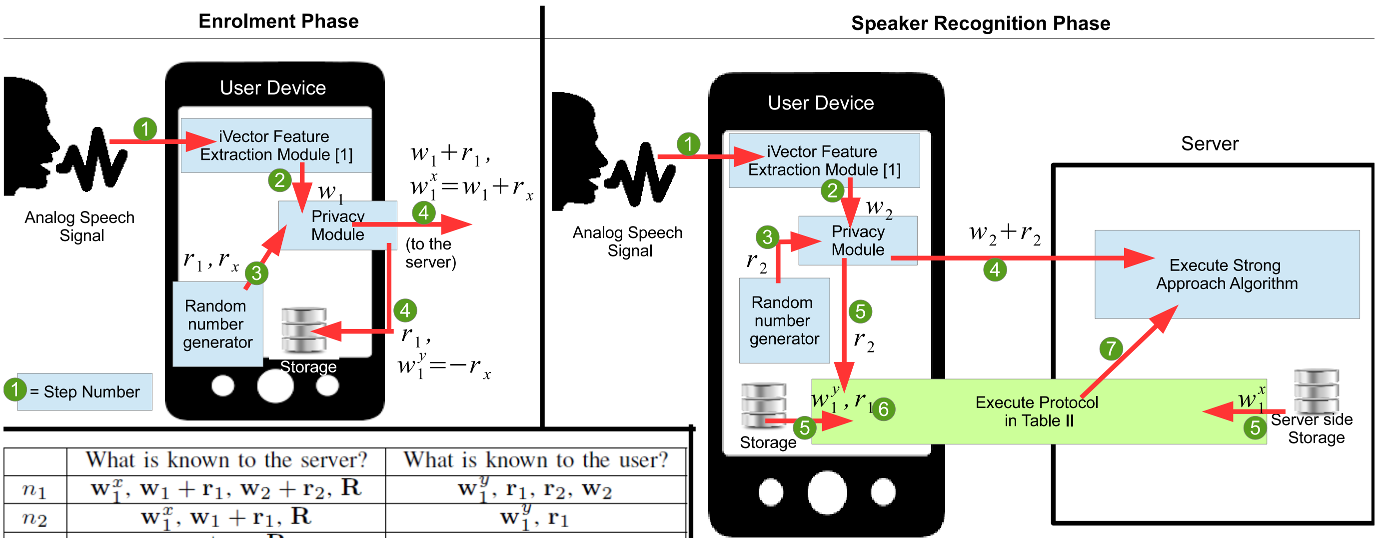
Then the user deletes $\mathbf{w}_1$ from the user device (the intuition behind this split is explained in Section VI-B). During the speaker verification phase, the user randomises the test feature vector $\mathbf{w}_2$ using a random vector $\mathbf{r}_2$ and sends $\mathbf{w}_2+\mathbf{r}_2$ to the server and keeps $\mathbf{r}_2$.

Then the server uses $\mathbf{w}_1+\mathbf{r}_1$, and $\mathbf{w}_2+\mathbf{r}_2$ to compute (3) as follows:

$$\begin{aligned}
& score(\mathbf{w}_1+\mathbf{r}_1,\mathbf{w}_2+\mathbf{r}_2)\\
=\ & \frac{(\mathbf{w}_1+\mathbf{r}_1)^T\mathbf{R}(\mathbf{w}_2+\mathbf{r}_2)}{\sqrt{(\mathbf{w}_1+\mathbf{r}_1)^T R(w_1+\mathbf{r}_1)}\sqrt{(\mathbf{w}_2+\mathbf{r}_2)^T\mathbf{R}(w_2+\mathbf{r}_2)}},\\
=\ & \frac{\mathbf{w}_1^T\mathbf{R}\mathbf{w}_2+n_1}{\sqrt{\mathbf{w}_1^T\mathbf{R}\mathbf{w}_1+n_2}\sqrt{\mathbf{w}_2^T\mathbf{R}\mathbf{w}_2+n_3}},
\end{aligned}\tag{5}$$

where

$$\begin{aligned}
n_1 &= \mathbf{w}_1^T\mathbf{R}\mathbf{r}_2+\mathbf{r}_1^T\mathbf{R}\mathbf{w}_2+\mathbf{r}_1^T\mathbf{R}\mathbf{r}_2,\\
&= \mathbf{w}_1^{x^T}\mathbf{R}\mathbf{r}_2+\mathbf{w}_1^{y^T}\mathbf{R}\mathbf{r}_2+\mathbf{r}_1^T\mathbf{R}\mathbf{w}_2+\mathbf{r}_1^T\mathbf{R}\mathbf{r}_2, && (6)\\
n_2 &= \mathbf{w}_1^T(2\mathbf{R})\mathbf{r}_1+\mathbf{r}_1^T\mathbf{R}\mathbf{r}_1,\\
&= \mathbf{w}_1^{x^T}(2\mathbf{R})\mathbf{r}_1+\mathbf{w}_1^{y^T}(2\mathbf{R})\mathbf{r}_1+\mathbf{r}_1^T\mathbf{R}\mathbf{r}_1, && (7)\\
n_3 &= \mathbf{w}_2^T(2\mathbf{R})\mathbf{r}_2+\mathbf{r}_2^T\mathbf{R}\mathbf{r}_2. && (8)
\end{aligned}$$



	What is known to the server?	What is known to the user?
n_1	$\mathbf{w}_1^x$, $\mathbf{w}_1+\mathbf{r}_1$, $\mathbf{w}_2+\mathbf{r}_2$, $\mathbf{R}$	$\mathbf{w}_1^y$, $\mathbf{r}_1$, $\mathbf{r}_2$, $\mathbf{w}_2$
n_2	$\mathbf{w}_1^x$, $\mathbf{w}_1+\mathbf{r}_1$, $\mathbf{R}$	$\mathbf{w}_1^y$, $\mathbf{r}_1$
n_3	$\mathbf{w}_2+\mathbf{r}_2$, $\mathbf{R}$	$\mathbf{r}_1$, $\mathbf{r}_2$, $\mathbf{w}_2$

Figure 1. Message flow diagram of the proposed algorithm. Left figure shows the enrolment steps, right figure shows the verification steps, and the table shows the parameters that are known only to the user and the parameters known only to the server.

In the numerator of (5), the true value $\mathbf{w}_1^T\mathbf{R}\mathbf{w}_2$ has been randomised by n_1. Similarly, in the denominator of (5), the true values $\mathbf{w}_1^T\mathbf{R}\mathbf{w}_1$ and $\mathbf{w}_2^T\mathbf{R}\mathbf{w}_2$ have been randomised by n_2, and n_3, respectively. In order to correctly verify the user, the server needs to calculate n_1, n_2, and n_3. However, the server does not have all the variables to correctly computes n_1, n_2, and n_3. The table in Figure 1 shows all the variables that are known only to the server and known only to the user.

Therefore, the user and server need to compute n_1, n_2, and n_3 jointly without leaking any sensible information to each other (i.e., secure two-party computation [15]). Lets define six vectors $\mathbf{u}_1$, $\mathbf{s}_1$, $\mathbf{u}_2$, $\mathbf{s}_2$, $\mathbf{u}_3$, and $\mathbf{s}_3$ as follows:

$$\begin{aligned}
\mathbf{u}_1 &= \left[\mathbf{r}_2^T \ vec(\mathbf{r}_2\mathbf{w}_1^{yT} + \mathbf{w}_2\mathbf{r}_1^T + \mathbf{r}\mathbf{r}_1^T)\right]^T \in \mathbb{R}^{(d+d^2)\times 1},\\
\mathbf{s}_1 &= \left[\mathbf{w}_1^{xT}\mathbf{R} \ vec(\mathbf{R})^T\right]^T \in \mathbb{R}^{(d+d^2)\times 1},\\
\mathbf{u}_2 &= \left[\mathbf{r}_1^T \ vec(\mathbf{r}_1\mathbf{w}_1^y)^T \ vec(\mathbf{r}_1\mathbf{r}_1^T)^T\right]^T \in \mathbb{R}^{(d+2d^2)\times 1},\\
\mathbf{s}_2 &= \left[2\mathbf{w}_1^{xT}\mathbf{R} \ vec(2\mathbf{R})^T \ vec(\mathbf{R})^T\right]^T \in \mathbb{R}^{(d+2d^2)\times 1},\\
\mathbf{u}_3 &= \left[vec(\mathbf{r}_2\mathbf{w}_2^T)^T \ vec(\mathbf{r}_2\mathbf{r}_2^T)^T\right]^T \in \mathbb{R}^{2d^2\times 1},\\
\mathbf{s}_3 &= \left[vec(2\mathbf{R})^T \ vec(\mathbf{R})^T\right]^T \in \mathbb{R}^{2d^2\times 1}.
\end{aligned}$$

From the table in Figure 1, the vectors $\mathbf{u}_1$, $\mathbf{u}_2$, and $\mathbf{u}_3$ can be obtained by the user without interacting with the server. Similarly, the vectors $\mathbf{s}_1$, $\mathbf{s}_2$, and $\mathbf{s}_3$ can be obtained by the server without interacting with the user. Hence, the equations (6) - (8) can be modified into

$$n_1 = \mathbf{u}_1^T\mathbf{s}_1, \ n_2 = \mathbf{u}_2^T\mathbf{s}_2, \ \& \ n_3 = \mathbf{u}_3^T\mathbf{s}_3. \tag{9}$$

To calculate n_1, n_2, and n_3, the user and server need to interact with each other. The following subsection explains this procedure.

E. The privacy-preserving scalar product algorithm

Since the server is not a trusted entity, the user cannot send the vectors $\mathbf{u}_1$, $\mathbf{u}_2$, and $\mathbf{u}_3$ to the server in the plain domain. Similarly the server cannot send $\mathbf{s}_1$, $\mathbf{s}_2$, and $\mathbf{s}_3$ to the user in the plain domain. To compute the required scalar products in (9), the user and server follow privacy-preserving protocol where no party can learn the other party's input. At the end of the protocol server should be able to obtain (9). This can be achieved by the privacy-preserving scalar product algorithm in Table II [18].

The user and server jointly execute the protocol in Table II three times to compute (9). Initially the user generates a number of random values to mask its input vector $\mathbf{a}$ (= $\mathbf{u}_1$ for first execution) and obtains masked vector $[C_1, C_2, \dots, C_n]$. As these masking operations use modulo reduction, the server cannot reverse engineer and reveal the user's input data from $[C_1, C_2, \dots, C_n]$ (refer [18] for the formal security proof).

Upon receiving $[C_1, C_2, \dots, C_n]$, the server now performs multiplication operations to get $[D_1, D_2, \dots, D_n]$. These values are then added through modulo addition followed by masking operation using γ and this is send to user. The user obtains $\mathbf{a}^T\mathbf{b} + \gamma$ using the secret key $s^{-1} \ mod \ p$. Finally the server receives $\mathbf{a}^T\mathbf{b} + \gamma$ from user and subtracts γ to get $\mathbf{a}^T\mathbf{b}$ (i.e., $= \mathbf{u}_1^T\mathbf{s}_1$). Message flow diagram of the proposed algorithm is shown in Figure 1.

V. Performance Analysis

In this section, we describe the dataset used in the experiment and present results for the experiments performed using both the traditional approach, i.e., without privacy and proposed approach followed by the complexity, security, and privacy analysis.

A. The dataset

TIMIT speech corpus [6] has been used to evaluate the accuracy and reliability of the proposed algorithm. The TIMIT

Table II
PRIVACY-PRESERVING SCALAR PRODUCT ALGORITHM [18].

Input by User: $\mathbf{a} = [a_1, \ldots, a_n]^T \in F_q^n$
and **Server:** $\mathbf{b} = [b_1, \ldots, b_n]^T \in F_q^n$
Output to Server: $\mathbf{a}^T\mathbf{b}$

User performs the following operations:
Given security parameters k_1, k_2, k_3, k_4,
choose two large primes α, p
such that $|p| = k_1$, $|\alpha| = k_2$, set $a_{n+1} = a_{n+2} = 0$
Choose a large random number $s \in Z_p$, and $n+2$ random numbers c_i, $i = 1, 2, ..., n+2$, with $|c_i| = k_3$
for each a_i, $i = 1, 2, ..., n+2$
Compute
$C_i = s(a_i.\alpha + c_i)\ mod\ p,\ \ a_i \neq 0$
$C_i = sc_i\ mod\ p,\ \ a_i = 0$
end for
keeps $s^{-1} mod\ p$ secret,
and send $(\alpha, p, C_1, \ldots, C_{n+2})$ to Server

Now Server executes the following operations
set $b_{n+1} = b_{n+2} = 0$
for each b_i, $i = 1, 2, ..., n+2$
Compute
$D_i = b_i.\alpha.C_i\ mod\ p,\ \ b_i \neq 0$
$D_i = r_i.C_i\ mod\ p,\ \ b_i = 0,$
where r_i is a random number with $|r_i| = k_4$
end for
compute $D = \sum_{i=1}^{n+2} D_i + \gamma\ mod\ p$
and send D back to User where $|\gamma| > |\sum_{i=1}^{n+2} a_i.b_i|$

Now User computes
$E = s^{-1}.D\ mod\ p$ and get $\mathbf{a}^T\mathbf{b} + \gamma$
$= \sum_{i=1}^{n} a_i.b_i + \gamma = \frac{E-(E\ mod\ \alpha^2)}{\alpha^2}$
and send $\mathbf{a}^T\mathbf{b} + \gamma$ to Server

Now Server obtains
$\mathbf{a}^T\mathbf{b}$ by subtracting γ from $\mathbf{a}^T\mathbf{b} + \gamma$
end procedure

speech corpus contains broadband recordings (each lasts for around 3 seconds) of 630 speakers of eight major dialects of American English. Each speaker has 10 speech samples. Out of 10 samples, 8 were used to build the speaker model.

For experiment, the TIMIT data corpus has been split into two: 1) the first two dialect regions with 151 speakers for training and testing and 2) the last four dialect region with 277 speakers were used to build background model. Table III shows the statistics of the TIMIT dataset.

Table III
TIMIT DATABASE.

Dialect Region (DR)	#Male	#Female	**Total**
DR1	31	18	**49**
DR2	71	31	**102**
DR3	79	23	**102**
DR4	69	31	**100**
DR5	62	36	**98**
DR6	30	16	**46**
DR7	74	26	**100**
DR8	22	11	**33**
Total	**438**	**192**	**630**

B. Experiments on the TIMIT Database without privacy

To validate the proposed method, we first obtain the verification accuracy of the iVector algorithm on TIMIT dataset using the pre-divided speech samples shown in Table III.

C. Definitions

The next subsections present various tests we conducted to validate the proposed model. To facilitate the description of tests, lets introduce several definitions used in speaker verification to measure the performance: False Acceptance Rate (FAR), False Rejection Rate (FRR), Equal Error Rate (EER), and Detection Error Tradeoff (DET) curve[1].

FAR and FRR are the two types of errors considered in speaker recognition domain to measure the performance, and are defined as follows:

- FAR= $\frac{\text{Number of False Acceptance}}{\text{Total Number of Imposter Attempts}} \times 100\%$,
- FRR = $\frac{\text{Number of False Rejection}}{\text{Total Number of Geinune Attempts}} \times 100\%$,

where False Acceptance is when the system grants access to an impostor, and False Rejection is when the system denies access to an enrolled speaker. The EER is another criterion used to compare the performance of speaker verification systems. It represents the operating point where the FAR is equal to the FRR. DET curve has been used in speaker verification to view FAR, FRR, and EER on the same curve. The DET curve comprises FRR in the y-axis and FAR on the x-axis. The EER represents the point on the DET curve where both FRR and FAR are equal.

D. Baseline Test

As described above, there are 151 users enrolled at the server. There are two speech samples available for each user for verification. To test the performance of the traditional (i.e., without privacy constraints) speaker recognition, the following two tests are conducted:

1) Genuine Attempts:- Client-Client: In this test, for each speaker, the score is calculated using the speaker's speaker model against the speaker's two test utterances. Hence, scores for $151 \times 2 = 302$ tests are obtained using (3).

2) Imposter Attempts:- Imposter-Client: In this test, each speaker's test utterances are tested against other 150 users' speaker models. This leads to $151 \times (151 - 1) \times 2 = 45300$ tests and the score for each test has been obtained using (3). Figure 2 shows the distribution between genuine attempts and imposter attempts tests. When the threshold $\theta = 1.34$ the equal error rate (EER) is 6.5%. We will use this result as a benchmark to compare the performance of the proposed algorithm.

E. Testing the proposed algorithm

Same experimental protocols described in Section V-D has been repeated to test the proposed algorithm. Since the privacy-preserving protocol in Table II is suitable for integers, the decimal values in speaker models and test feature vectors

[1]DET curves are plotted using NIST DET-ware-v2.1 tool: Available On line: https://www.nist.gov/file/65996, Accessed on 5th of June, 2018.

Table IV
SAMPLE DATA SHOWING THE EFFECTS OF SCALING, QUANTISATION AND RANDOMISATION.

Effect of Scaling (Supporting Data for Figure 3)				Effect of Randomisation (Supporting Data for Figure 4)		
Sample iVector Values	Scaling (x100) and Integer Quantisation	Scaling (x600) and Integer Quantisation	Scaling (x1000) and Integer Quantisation	Randomising with random number in the range of [-10 to 10]	Randomising with random number in the range of [-100 to 100]	Randomising with random number in the range of $[-10^6$ to $10^6]$
0.010924	1	6	11	7	23	447961
0.017854	1	10	17	8	-6	359424
-0.027501	-2	-16	-27	-33	25	310168
0.017645	1	10	17	8	77	-674759
-0.025132	-2	-15	-25	-29	-88	-762030
Sample elements of Projection Matrix $\mathbf{R}$	Scaling (x100) and Integer Quantisation	Scaling (x600) and Integer Quantisation	Scaling (x1000) and Integer Quantisation	Randomising with random number in the range of [-10 to 10]	Randomising with random number in the range of [-100 to 100]	Randomising with random number in the range of $[-10^6$ to $10^6]$
2.080734	208	1248	2080	2088	2079	-1191
1.714698	171	1028	1714	1719	1704	921203
1.098638	109	659	1098	1095	1128	-318130
-1.406361	-140	-843	-1406	-1397	-1364	169130
-1.801433	-180	-1080	-1801	-1811	-1750	-554177

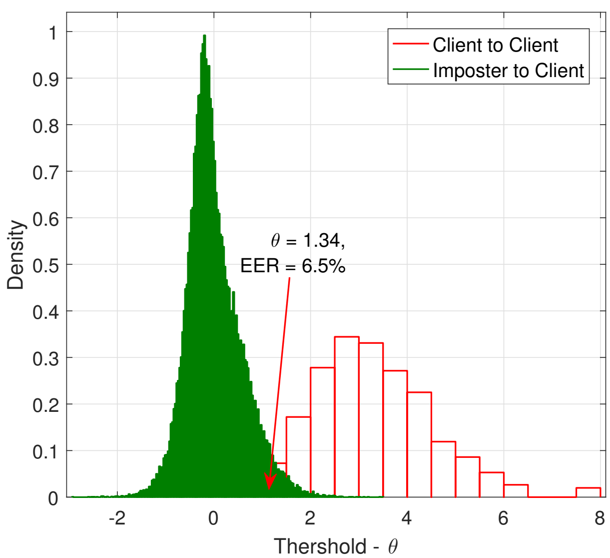


Figure 2. Score distribution of genuine and imposter tests.

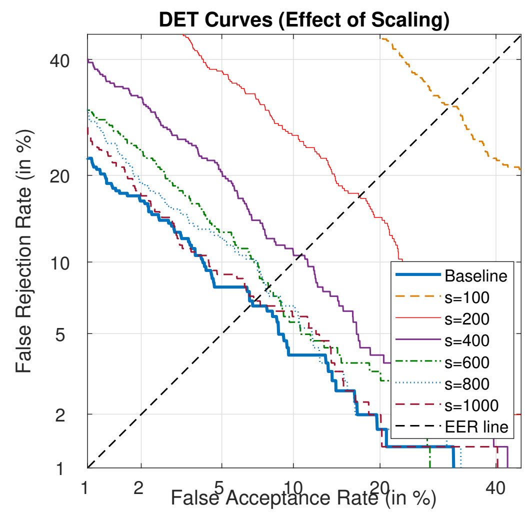


Figure 3. The accuracy of the proposed scheme for various scaling factors.

must be scaled to integers via scaling and quantisation operations followed by randomisation.

Table IV shows few examples for scaling, quantisation and randomisation using the values of ivectors (i.e., $\mathbf{w}_1$ or $\mathbf{w}_2$) and projection matrix (i.e., $\mathbf{R}$). When the scaling factor increases, the effect of quantisation is decreasing e.g., the sample value in the first row in Table IV (0.010924) is almost half of the value in the second row (0.017854). However, when scaling factor is equal to 100 (2nd column), both the values became equal. When the scaling factor has been set to 1000 (fourth column), the ratio between both the values is getting closer to the correct ratio.

Once the elements of input vectors are scaled and quantised to nearest integers, the integers go through randomisation process using random integers. The last three columns of Table IV shows how the scaled values are randomised by different sizes of random numbers. The fifth column in Table IV shows how the scaled elements in fourth column are randomised using random numbers between 10 and -10. Similarly last column in Table IV shows how the scaled elements in fourth column are randomised using random numbers between 10^6 and -10^6.

In order to evaluate the impact of scaling and rounding operations, we repeated the two tests conducted in Section V-D but using the proposed algorithm for scaling factors $s = 100$, $s = 200$, $s = 400$, $s = 600$, $s = 800$, and $s = 1000$ and randomisation with random numbers in the range of -10^6 to 10^6. Figure 3 shows the DET curves for the above scaling factors. When the scaling factor increases from 100 to 1000, the accuracy of the proposed scheme approaches the benchmark accuracy. For a scaling factor $s = 1000$, the proposed algorithm illustrates identical recognition as the benchmark. This validates that the proposed model does not compromise the accuracy.

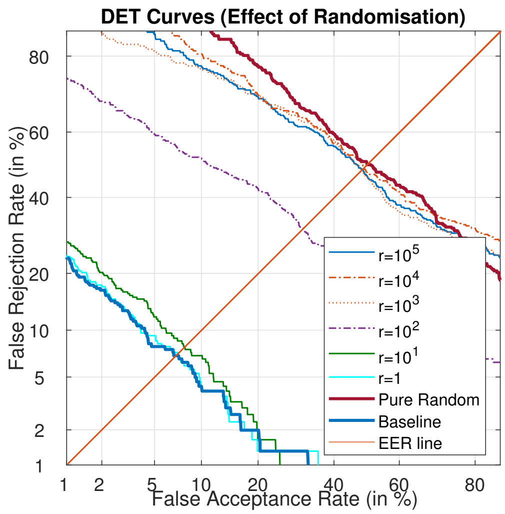


Figure 4. The accuracy of the proposed scheme for various scaling factors.

In order to test the effect of randomisation (or to answer why the scaled and quantised input elements are randomised using large random numbers (10^6) instead of 10), we repeated the baseline test (experiment conducted in Section V-D) but with a randomised test feature vector and projection matrix. We used different size of random values ranging from 1 to 10^5 to randomise the elements of test features and projection matrix (i.e., similar to 4, 5, and sixth columns in Table IV). We also tested the baseline model with pure random vectors (i.e., generated independently of speech) as test features. As shown in Figure 4, when the size of the random values decreases, the accuracy increases. When the size of the random values are in the range of 10^5, there is no significant difference in accuracy between random testing (Pure Random in the Figure 4) and randomised testing. It means if the input elements are not masked by large random numbers then it is possible for the adversary to infer the identity of the input samples. However, when randomising the test features with larger random numbers (i.e., 10^5 in this experiment), the accuracy of the system is closer to the accuracy of pure random inputs. It means when the input elements are randomised by large random numbers, there is no different in statistical properties between pure random values and randomised input values.

F. Complexity Analysis

The proposed privacy-preserving algorithms require additional mathematical operations to protect the parameters from the untrusted server. The BA algorithm does not require any additional mathematical operations except addition and subtraction, hence we assume the complexity of BA is same as the traditional (i.e., without privacy constraint) algorithm. Lets denote the time complexity for one multiplication as t_{mul} and for square-root as $\sqrt{.}$. Since the ivector feature extraction is common for both the traditional and proposed SA algorithms, lets compare the complexity of both the algorithm after the feature extraction.

In the traditional algorithm, once the ivector has been extracted, the user device does not require to perform any operations. However, the server needs to compute (3) which requires $3(l^2 + l)t_{mul} + 2\sqrt{.}$ operations if the ivectors are $l-$dimensional. In the proposed SA algorithm, the user device and server need to perform some additional computations to obtain (9) via scalar product algorithm in Figure II. To execute the algorithm in Figure II, the server needs to perform $(2n{+}4)t_{mul}$ and the user device needs to perform $(2n{+}5)t_{mul}$ if the dimension of the input vectors is n.

In order to compute the scalar products in (3), the user and server need to invoke the protocol illustrated in Figure II twice (to obtain n_1 and n_3). It should be noted that n_2 in (3) can be calculated offline and pre-stored at the server side as it does not require speaker recognition parameters. Hence the total computational cost for the user and server would be $2(2n + 5)t_{mul}$ and $2(2n+4)t_{mul} + 3(l^2+l)t_{mul} + 2\sqrt{.}$, respectively. Hence the computational *overheads* for the user and server are $2(2n{+}5)t_{mul}$ and $2(2n{+}4)t_{mul}$, respectively (i.e., subtract the traditional algorithm's complexity from proposed algorithm's complexity). It is obvious from these overheads that the user device needs to do more additional work than the server in order to protect the privacy.

In order to evaluate the complexity, we implemented the proposed scheme on a computer - Intel(R) Core(TM) i5-4210U CPU @1.70GHz with 8GM RAM - using Matlab 2016a. We modified the iVector library from GitHub (github.com/pedrocolon93/ivectormatlabmsrit) to implement the proposed scheme. Using this implementation, we tested the complexity of the proposed scheme for different values of n. We performed 50 iterations of the proposed scheme by varying the input size n from 10^3 to 10^6. The average time taken is illustrated in Figure 5. The computational time increases linearly up to $n = 10^5$. From $n = 10^5$, the time increases exponentially due to processing large amount of data in a sequential order. This problem can be solved by parallel processing by executing the scalar product computation in multiple threads. For example, if $n = 6$, instead of calculating $[a_1\ a_2\ a_3\ a_4\ a_5\ a_6].[b_1\ b_2\ b_3\ b_4\ b_5\ b_6]^T$ sequentially, the problem can be split into two: $[a_1\ a_2\ a_3].[b_1\ b_2\ b_3]^T$ and $[a_4\ a_5\ a_6].[b_4\ b_5\ b_6]^T$. The results can be added in the end.

For the experiment in Section V, the dimension of iVector has been set to $d = 200$ [1]. Therefore the sizes of the input vectors in (9) for Table II, are in the range of $n = 40000$ to $n = 80000$. This is within the linear time complexity range i.e., the incurred computational overhead is less than 0.05 seconds for both the user and server.

VI. Security and Privacy Analysis

Since the proposed algorithm relies on randomisation, the following subsections provide a formal security proof for the proposed randomisation algorithm in Section VI-A and a privacy analysis for the proposed SA algorithm in Section VI-B.

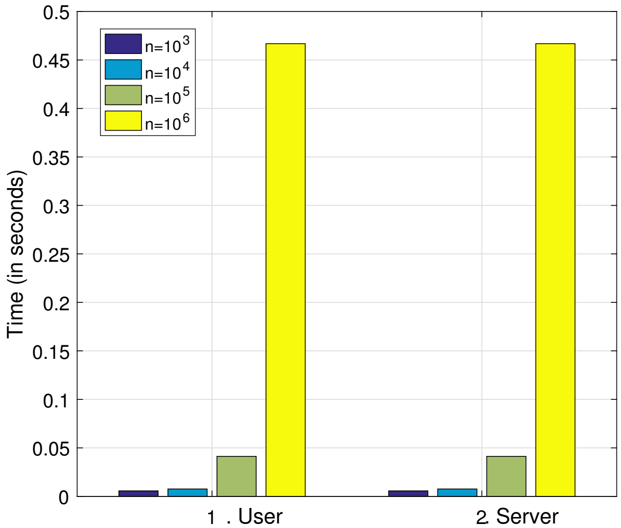


Figure 5. Computational overheads of the proposed scheme for user and server.

A. Security model and proof for the proposed randomisation algorithm in Section VI-A

This section proves that the proposed randomisation algorithm in Section IV-A satisfies the information-theoretic security. Denote a mapping $f : \mathcal{M} \times \mathcal{S} \longmapsto \mathcal{R}$. We call such a mapping f over a message space $\mathcal{M}$ to be perfectly random if and only if for an uniform probability distribution s over $\mathcal{S}$, every message $m \in \mathcal{M}$ and every randomised message $r \in \mathcal{R}$, $Pr[M = m|R = r]$ is constant greater than zero, i.e., looking at the randomised message no one can guess the message. Theorem 1 shows that Algorithm 1 in Section IV-A attains perfect randomisation.

Theorem 1: Let $\mathcal{M} = [-a, a] \cap \mathbb{Z}$ and $\mathcal{S} = [v_1, v_2] \cap \mathbb{Z}$ be two sets such that $a < v_1 < v_1 + a < v_2$. Also let $\mathcal{R} = \{m + s; m \in \mathcal{M}, s \in \mathcal{S}, v_1 + a \leq m + r \leq v_2 - a\}$. Then for any $r \in \mathcal{R}$, $Pr[M = m|R = r] = \frac{1}{|\mathcal{S}|}$.

Proof: Let $r \in \mathcal{R}$ and $m \in \mathcal{M}$. Then, it is easy to check that $v_1 \leq r - m \leq v_2$. So,

$$\begin{aligned} Pr[M = m|R = r] &= Pr[r - s = m|R = r] \\ &= Pr[r - s = m] \\ &= Pr[s = r - m] \\ &= \frac{1}{|\mathcal{S}|} \end{aligned}$$

■

The perfect randomness leads to adaptive indistinguishability. But before giving the proof, we first consider the definition of adaptive indistinguishability game.

Definition 1: $[Gm\_Ad_{\mathcal{A},\pi}(1^s)]$

1. The adversary $\mathcal{A}$ is given oracle access to $Enc_s(.)$ and outputs a pair of messages $m_0, m_1 \in \mathcal{M}$ of the same length.
2. Random bit $b \leftarrow \{0, 1\}$ is chosen, and $s \leftarrow \mathcal{S}$ is also chosen randomly. Then a ciphertext $r = s + m_b$ is computed and given to $\mathcal{A}$.
3. The adversary $\mathcal{A}$ continues to have oracle access to $Enc_s(.)$ and outputs a bit b'.
4. The output of the experiment is defined to be 1 if $b' = b$, and 0 otherwise. In case $Gm\_Ad_{\mathcal{A},\pi}(1^s) = 1$, we say that $\mathcal{A}$ succeeded.

Definition 2: An encryption scheme, denoted by $\pi = (KeyGen, Enc, Dec)$, is said to be adaptively secure under chosen plain text attack if for all probabilistic polynomial time adversaries $\mathcal{A}$, there exists a negligible function $negl$ such that $Pr[Gm\_Ad_{\mathcal{A},\pi}(1^s) = 1] \leq \frac{1}{2} + negl(s)$, where the probability is taken over the random coins used by $\mathcal{A}$, as well as the random coins used in the game.

Let us consider the encryption scheme $\pi' = (Gen, Enc_s, Dec_s)$ such that $Gen()$ samples uniformly at random a key s from the set $\mathcal{S}$, i.e., $Pr[S = s] = \frac{1}{|\mathcal{S}|}$. For any $m \in \mathcal{M}$, $Enc_s(m) = m + s$ and for any $r \in \mathcal{R}$, $Dec_s(r) = r - s$. Following theorem shows that this scheme is adaptively secure.

Theorem 2: π' is adaptively secure under chosen plain text attack.

Proof: Let $|\mathcal{S}| \approx 2^\lambda$. Let us consider the game $Gm\_Ad_{\mathcal{A},\pi'}(1^\lambda)$. Note that $\mathcal{A}$ being a polynomial adversary, may call the encryption oracle polynomial (in λ) number of times before receiving challenge cipher. Let this polynomial be $p(\lambda)$. Let *Repeat* be the event that the key used in challenge phase is used in any of the previous calls.

Note that $Pr[(Gm\_Ad_{\mathcal{A},\pi'}(1^\lambda) = 1) \wedge \mathit{Repeat}] \leq Pr[\mathit{Repeat}] = \frac{p(\lambda)}{2^\lambda}$.

Also when *Repeat* does not occur, adversary has absolutely a random view and thus,
$Pr[(Gm\_Ad_{\mathcal{A},\pi'}(1^\lambda) = 1) \wedge \overline{\mathit{Repeat}}] = Pr[\overline{\mathit{Repeat}}] \times Pr[(Gm\_Ad_{\mathcal{A},\pi'}(1^\lambda) = 1)|\overline{\mathit{Repeat}}] \leq Pr[(Gm\_Ad_{\mathcal{A},\pi'}(1^\lambda) = 1)|\overline{\mathit{Repeat}}] = \frac{1}{2}$.
So,

$$\begin{aligned} &Pr[Gm\_Ad_{\mathcal{A},\pi'}(1^\lambda) = 1] \\ &= Pr[(Gm\_Ad_{\mathcal{A},\pi'}(1^\lambda) = 1) \wedge \mathit{Repeat}] + \\ &\qquad Pr[(Gm\_Ad_{\mathcal{A},\pi'}(1^\lambda) = 1) \wedge \overline{\mathit{Repeat}}] \\ &\leq \frac{p(\lambda)}{2^\lambda} + \frac{1}{2} \end{aligned}$$

We note that $\frac{p(\lambda)}{2^\lambda}$ is negligible in λ which completes the proof.

■

B. Privacy Analysis privacy analysis for the proposed SA algorithm in Section VI-B

The ultimate aim of the proposed algorithms is to protect user voice biometrics stored at and transmitted to the server. Both the proposed BA and SA algorithms randomise the voice feature vectors using random vectors and invoke two-party computation. During the two-party computations, if the user and server exploit the proposed randomisation algorithm to mask the data, as shown in the previous section, then the randomised data is information theoretically secure. Hence lets prove that the proposed SA algorithm does not leak any unintended data during the two-party computation.

1) Privacy proof for SA algorithm: During the enrolment process, the user device randomises the ivector $\mathbf{w}_1$ using the proposed randomisation algorithm and send only the randomised ivector $\mathbf{w}_1 + \mathbf{r}_1$ and $\mathbf{w}_1^x = \mathbf{w}_1 + \mathbf{r}_x$ to the server and stores the random numbers $\mathbf{r}_1$ and $-\mathbf{r}_x$ in the user device. Then the user device deletes $\mathbf{w}_1$ and $\mathbf{r}_x$. After this enrolment process, the server holds $\mathbf{w}_1 + \mathbf{r}_1$ and $\mathbf{w}_1^x = \mathbf{w}_1 + \mathbf{r}_x$ while the user holds $\mathbf{r}_1$ and $\mathbf{w}_1^y = -\mathbf{r}_x$. Hence, even if the server has been compromised by an adversary after the enrolment, it is information-theoretically infeasible for the adversary to retrieve $\mathbf{w}_1$ from $\mathbf{w}_1 + \mathbf{r}_1$ and $\mathbf{w}_1^x = \mathbf{w}_1 + \mathbf{r}_x$ without $\mathbf{r}_1$ and $\mathbf{r}_x$. Similarly, if the user device which holds $\mathbf{r}_1$ and $\mathbf{w}_1^y = -\mathbf{r}_x$ is being compromised by an adversary, it is information-theoretically infeasible for the adversary to retrieve $\mathbf{w}_1$. To launch a successful attack, the adversary needs to compromise both the server and user device, which is an extreme condition and out of the scope of this paper.

During the verification stage, the ivector $\mathbf{w}_2$ is again randomised into $\mathbf{w}_2 + \mathbf{r}_2$ where the user device keeps $\mathbf{r}_2$ and the server gets $\mathbf{w}_2 + \mathbf{r}_2$. Similar to the above discussion, $\mathbf{w}_2$ cannot be obtained from $\mathbf{w}_2 + \mathbf{r}_2$. However, in order to get the true score, the user device and server need to perform two-party computation using the privacy-preserving scalar product algorithm in Figure II. As shown in [18], the security of the algorithm in Figure II relies on randomisation (User's inputs $a_1, a_2, \ldots$ are randomised by large random numbers $c_1, c_2, \ldots$) and achieves information-theoretic security.

C. Privacy Leakage Analysis

The previous section provided a theoretical proof showing that the proposed algorithm is information theoretically secure. To visualise this and analyse whether the randomised features still preserve the statistical properties of speech feature, a numerous experiments are conducted in this section. We can broadly split the parameters required for a successful verification into four: 1) voice 2) randomised iVector ($\mathbf{w}_1 + \mathbf{r}_1$) 3) parameters stored on the user device and 4) server-side parameters. In order to evaluate the strength of the proposed algorithm, the following four attacks scenarios are considered:

1. Compromised user device attacks
2. Compromised server attacks
3. Compromised user voice attacks
3. Pure random attacks

1) Compromised user device attacks: In this attack, the adversary has access to the user device and the parameters stored during the enrolment. But do not have access to the user voice to generate legitimate test ivector. Hence, the adversary tries to combine the parameters from the compromised user device with the test features of *other users*. Then the adversary tries to verify against the compromised user's speaker model residing at the server. To evaluate this, $2 \times 150 \times 151$ tests [300 test utterances from other users are combined with the parameters of the compromised user device and this is repeated for all the users] are conducted and the corresponding decision scores are obtained.

2) Compromised server attacks: In this attack, the adversary has access to the randomised ivectors $\mathbf{w}_1 + \mathbf{r}_1$ of all the users stored at the server. Let's also assume that the adversary holds the feature vectors of all users but neither know the corresponding ivectors stored at the server or keys stored at the user device. Now the attacker uses these randomised ivectors to simulate a speaker verification system and tries to find out the corresponding users for each stolen randomised ivector. Hence, the adversary tries to measure the decision score by applying those features against each and every randomised ivector. Again $2 \times 151 \times 151$ tests are conducted and the corresponding decision scores are obtained.

3) Compromised user voice attacks: In this attack, the attacker has access to the user's voice recording but does not have access to the parameters stored at the user device. Now the attacker generates random numbers and randomises the voice feature and tries to impersonate. Hence, this experiment generates 300 random vectors same size as the feature to obtain 300 randomised test features. To analyse the performance, we conduct 300×151 tests are conducted and the corresponding decision scores are obtained.

4) Pure random attacks: In this final test, the traditional solution has been considered but instead of using the legitimate test features, purely random vectors in the same domain and same size as the legitimate test ivector used. Hence, we generate 300 random vectors for each user and conducted 300×151 tests.

We now use the decision scores obtained by all these tests and the baseline scores, and displayed them in Figure 6. Figure 6 displays the DET curves for the above attacks. In the same figure, we displayed the baseline model. Interestingly, from Figure 6, the equal error rate for all four attacks are around 50% and there is no significant difference between the first three attacks against the pure random attacks (the fourth attacks). This clearly shows that there are no advantages for an adversary who compromises the parameters of the proposed systems than just launching random attacks. This concludes that the proposed algorithm is information theoretically secure and all four parameters must be combined to reveal the statistical properties.

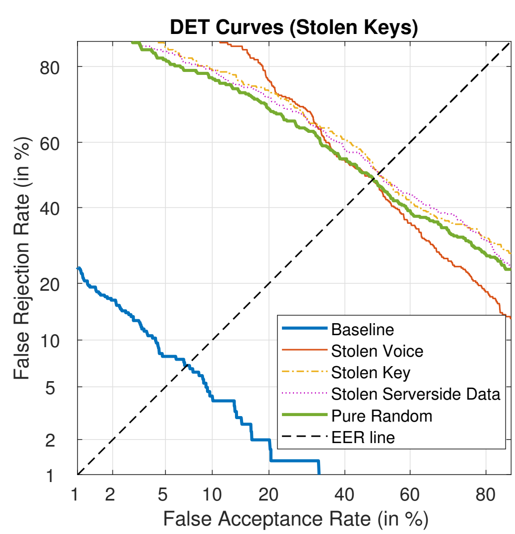


Figure 6. Stolen key attack scenarios

VII. Conclusion

In this paper an efficient privacy preserving speaker verification protocol is proposed. To achieve better efficiency and privacy, the proposed solution algorithmically redesigned the iVector and linear discriminant analysis based speaker verification techniques to incorporate randomness without affecting the final outcome. The proposed scheme is based on randomisation technique and it only relies on multiplication and addition. In this scheme, two parties involved, the user and the server, need to perform verification interactively. In addition It is proved using information-theoretic security that the algorithm is secure. It is also shown empirically that the proposed scheme provides good overall accuracy without increasing the computational overhead.

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