Estimating Uniqueness of Human Voice Using I-Vector Representation

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Abstract—We study the individuality of human voice with respect to a widely used feature representation of speech utterances, namely, the i-vector model. As a first step toward this goal, we compare and contrast uniqueness measures proposed considering different biometric modalities. Then, we introduce a more appropriate uniqueness measure that evaluates the entropy of i-vectors while taking into account speaker level variations. Estimates are obtained on two newly generated datasets designed to capture variabilities between and within speakers. The first dataset speech samples of more than 20 thousand speakers obtained from TEDx Talks videos. The second one includes samples of more than one and a half thousand actors that are extracted from movie dialogues. By using this data, we analyzed how several factors, such as the number of speakers, number of samples per speakers, and different levels of within-speaker variation affect estimates. Most notably, we determined that the discretization of i-vector elements does not necessarily cause a reduction in speaker recognition performance. Our results show that the degree of uniqueness offered by i-vector based representation may reach 43-52 bits in a confined setting; however, under less constrained variations estimates reduce significantly to 13-20 bit level, depending on coarseness of quantization.

I. INTRODUCTION

Biometric solutions have increasingly become a key component of security systems that govern everyday processes of daily and public life. Today, most smartphones utilize at least one of fingerprint, facial, or iris recognition as the main method for user verification. Behavioral biometrics are at the core of enterprise information systems to detect anomalies in user interactions with systems and to provide initial as well as continuous authentication. This widespread adoption of biometrics for implementing authentication and user identification is evidently due to the fact that biometric traits are unique to the individual, that they are sufficiently invariant, and that they can easily be captured and processed with minimal user intervention.

Among all types of biometric technologies, there is a more visible growth in the use of voice-based authentication and identification systems. This is partly due to well established expertise in audio signal representation and processing, which continues to further grow by advances in deep learning. But more importantly, it is due to various application contexts that involve speech-based user interactions where voice as a biometric modality is readily available. For example, in call center environments verifying the identity of a caller through voice offers a more convenient and cost-effective alternative to conventional knowledge-based authentication where the agent asks the caller a series of questions for the caller to answer. Moreover, for embedded sensor-enabled devices like wearables that have limited user interface there are only a few alternatives to voice for authentication. With the pervasive availability of voice assistants in everyday devices, such as smartphones and IoT devices, and the potential integration of voice technology within many applications, speaker verification capabilities will likely become even more important.

At its core, the use of voice biometric, or any other biometric modality for the general case, as part of security systems rests on uniqueness and individuality of such biometric data. Although this is correct in analog domain, digitization of biometric data through an error-prone measurement process that can be influenced by several environmental factors effectively introduces a limit on the discernible biometric information content. Hence, the success of attacks targeting such widely deployed systems potentially depend on the ability to exploit assumed capabilities of voice for authentication and identification tasks.

Voice authentication systems typically utilize a voice model (i.e., voiceprint) of the user. This model could be created in a text dependent or independent manner, and user verification is performed by matching the voiceprint extracted from a short utterance to a more reliable voiceprint created during the enrollment phase. One possible attack against these system includes the use of voice synthesis and conversion methods to generate the desired text in a voice that will produce a match with the target speaker, i.e., voice-spoofing attacks, [1]–[4]. This can be realized through a variety of methods all of which require access to voice samples of the target user with durations varying from a couple of minutes to several hours [5]–[7].

Since launching such an attack at scale requires large amount of samples from users, it is not practically feasible. A fraudster, however, can alternatively use other speakers voice samples to spoof the voice of a target speaker. For this purpose, the attacker can create a dictionary that spans a diverse range of voices, along with sufficient samples, and can quickly identify voice samples most similar to a given query voice sample to be used during spoofing. Unlike many other biometric modalities, it is relatively easy for fraudsters to capture voice for a large population. Not only large number of voice samples are available online, one can also acquire voice samples by systematically calling phone numbers. With robocalling and VoIP technology, such calls can be made at scale with very low cost. Hence viability of this attack depends largely on the difficulty of creating such a voice dictionary whose size will be in the order of unique voice models. This ultimately calls for evaluating the uniqueness of users’ voice
models which translates into an inquiry about the information content of a biometric modality.

Despite significant research in representation and matching of biometric data, uniqueness and individuality of biometric modalities have not been studied very thoroughly. This is in fact a relevant problem in a much larger context as biometrics like phenomena associated with embedded hardware, such as imaging sensors [8], speakers [9], microphones [10], accelerometers [11], gyroscopes [12], wireless transceivers [13] and CPUs [14], are constantly being observed with the assertion that these characteristics can also be used to support modalities including voice, iris, face, fingerprints. However, determining the amount of information contained in a biometric modality to their implication for user privacy.

To date, a number of studies have been undertaken to determine the amount of information contained in a biometric modality including voice, iris, face, fingerprints. However, measurements provided by different publications vary significantly. In the case of voice biometric, individuality estimates range between 14 bits [15] and 120 bits or higher depending on the length of speech samples used for measurements [16]. (That is, the number of unique human voices is in the order of 2\(^{14}\) or 2\(^{120}\).) Further, a similar pattern has been observed across other modalities, albeit to different extents [17]. For example, a fingerprint, the most mature and well established modality, is estimated to have an entropy between 12.7 [18] and 55 bits [19]. Similarly, estimates about the uniqueness of biometric face images vary between 12.6 [18] and 55 bits. Finally, iris biometric, which is considered to be the most reliable of all, is estimated to offer 249 [21] to 288 bits of information. Variations up to an order of magnitude (in the exponent) difference in above estimates indicate the need for a more systematic evaluation.

In fact, three factors play an important role in the discrepancy between reported results on distinctiveness of biometric modalities. Biometric data is almost always transformed into a feature space. Hence, an important source of variability is the choice of biometric feature representation. Since compact representation of a continuous variable can only be achieved at the expense of information loss, different representations of a biometric modality yield varying discriminative power. The other important factor contributing to difficulty in establishing the uniqueness of a biometric modality is quantification of biometric information. The inherent variability of a biometric modality combined with the measurement noise and the complexity of modelling high-dimensional feature representations hinder analytical tractability significantly. As a result, it becomes difficult to directly utilise the concept of entropy and alternative definitions were adopted to estimate the inherent entropy. The last source of variability concerns the dataset used for modelling and measurements. Essentially, the accuracy of estimates depends on how well a given dataset reflects the biometric diversity of users and the overall biometric variability exhibited by users. However, producing reliable, comprehensive public datasets is a very challenging task due to increasing privacy concerns.

To help close this gap, in this work, we study the problem of measuring the individuality of a biometric modality in the context of voice biometric. Towards this goal, our work brings all approaches to measuring distinctiveness of biometric modalities together and evaluates their strengths and weaknesses from the standpoint of generalizing these measures. Our approach to estimation of uniqueness differs from existing ones as it computes the entropy of speaker i-vectors while taking into account within-speaker variability and builds on a mutual information based formulation. Measurements are performed on quantized version of a widely used feature representation in speaker recognition, namely, the i-vector representation. Performance implications of operating in a discrete feature domain are also investigated.

To evaluate and compare our approach, we created two distinct benchmark datasets. One of these datasets include voice samples of close to 21 thousand speakers obtained from audio tracks of TEDx Talk videos, and the other includes samples of more than 1500 actors extracted from dialogues of 249 movies. The former dataset is mainly used to quantify how uniqueness estimates vary depending on number of speakers as well as the amount of speech samples available from each speaker. Whereas the latter is used to determine to what degree the true variability intrinsic to a speaker’s voice affects estimates. Overall, the data used in our experiments constitute the most comprehensive one used by a study of similar nature in its effort to better incorporate inter-speaker and within-speaker variability.

Our paper is organized as follows. In Section II we start by reviewing the work done in the field of speaker recognition and speaker verification with an emphasis on voice models proposed for speaker representation. This is followed by a qualitative description of approaches proposed for measuring individuality of a variety of biometric modalities and a discussion on their applicability to voice biometric in Section III. The details of our uniqueness estimation method are given in Section IV. The two datasets used in experiments along with the process we followed in their creation are described in Section V. The results of analysis and uniqueness estimates obtained considering a variety of settings are provided in Section VI. We finally conclude the paper with a discussion of our findings in Section VII.

II. Voice Models

The majority of speaker recognition systems deploys Mel-Frequency Cepstrum Coefficients (MFCCs) as the feature representation for speech signals. MFCCs provide spectral energy measurements over short-term frames of a speech signal with each measurement involving a vector of 10-20 coefficients [23]. These coefficients capture unique spectral characteristics of a speaker’s voice and the manner a speaker articulates different sounds in the language. To better capture the spectral dynamics of a speaker, the MFCC based feature vectors obtained from each frame are further augmented by the first-order and second-order derivatives of the coefficients.

In text-independent speaker recognition systems, speakers are most commonly characterized by modeling the distribution of their MFCC vectors by a mixture of Gaussians, i.e., a Gaussian Mixture Model (GMM) [24]. Therefore, each
A speaker model is represented by a set of GMM parameters $\lambda_i = \{w, \mu, \Sigma\}$ where $w$ represents the weights of a speaker’s Gaussian components, $\mu$ is the mean vector, and $\Sigma$ is the covariance matrix. In addition to speaker-specific models, a Universal Background Model (UBM) is created which is a similarly generated model from speech samples of a large set of speakers to represent general, speaker-independent feature characteristics. The speaker models and the UBM are used together to perform speaker verification [25]. In the resulting GMM-UBM system, a verification decision about an unknown speech sample is made through a likelihood ratio test which evaluates the degree of match between the known speaker model and the UBM.

This initial system is later further improved by a focus on better modeling of speaker related variations while compensating for undesired variabilities. With this objective, Campbell et al. introduced the concept of GMM mean supervector by stacking the mean vectors of each GMM component in a high-dimensional vector [26]. In this approach, essentially each speech utterance is mapped to a mean supervector $M$ which is further decomposed into a sum of speaker and channel-dependent components. By applying joint factor analysis, Kenny et al. [27] proposed modeling these components in $M$ as

$$M = m + V y + U x + D z$$

where $m$ is a speaker- and channel-independent supervector, $V$ is an eigenvoice matrix, $U$ is an eigenchannel matrix and $D$ is a residual matrix. The vectors $y$ and $z$ represent speaker-dependent factors whereas $x$ includes channel-dependent factors.

In [28], Dehak et al. introduced an alternative factor analysis model which resulted in a representation that is widely used by various state-of-the-art speaker recognition systems. In this framework, the GMM mean supervector $M$ associated with a speaker’s utterance is defined as

$$M = \mu_{UBM} + T_i$$

where $T$ is a total variability matrix containing the speaker and channel variability simultaneously, $\mu_{UBM}$ is a GMM mean supervector for the UBM which is a speaker-independent component similar to $m$ in Eq. (1), and $i$ is the identity vector (i-vector) that compactly represents all the variability in the supervectors. I-vectors have a dimension typically around 400 which can be further reduced through linear discriminant analysis.

Although there are a plurality of methods proposed for i-vector based speaker modeling and comparison, Gaussian Probabilistic Linear Discriminant Analysis (GPLDA) is the commonly employed one [29]. In the GPLDA approach, an i-vector is further modeled as

$$i = i_{offset} + \phi \beta + \epsilon_i$$

where $i_{offset}$ is a global offset, $\phi \beta$ is speaker-specific component, and $\epsilon_i$ is a residual term. The matrix $\phi$ represents the projection from the i-vectors to the underlying latent identity vector $\beta$ which is assumed to have a standard normal distribution. For speaker verification, a hypothesis test is performed to determine whether the underlying $\beta$ for the test i-vector is the same as those estimated from speaker i-vectors obtained during modeling. This is realized by computing a log-likelihood ratio based score between the test i-vector and i-vectors of all known speakers. The i-vector in question is then associated with the speaker that yields the highest average score.

With the advent of deep learning, more recently, deep neural network (DNN) architectures have also been used to build speaker models. This approach effectively utilizes the outputs of a layer of a DNN as feature vectors and keeps the rest of the overall verification system. The most successful of such proposals is the so-called x-vector representation which incorporated the idea of data augmentation to improve the robustness of DNN embeddings obtained at the last fully-connected layer [30]. Experimental evaluations show that use of x-vector representation will be a strong contender for future speaker verification systems.

Despite the advantages brought by the DL-based feature extraction approaches, the most important challenge in these approaches is the necessity of supervised training which is not required in the i-vector approach. Therefore, the convenience of avoiding supervision still is one of the strong aspects of the i-vector approach over alternative proposals. Moreover, it is demonstrated that both in the text-independent [31] and text-dependent [32] test scenarios the fusion of two systems improves the performance, indicating that two representations are complementary in nature. Overall, due to the widespread adoption of i-vector representation in today’s speaker recognition systems and the complementarity between the two representations, we focus on measuring the uniqueness of i-vector representation in this work.

### III. Uniqueness Estimation Approaches

The amount of discriminatory information present in a biometric modality has long been a focus of research. Early work mainly used the probability of false biometric matching, i.e. matching a given biometric to any other biometric sample by chance for a single user verification attempt, as a measure for estimating individuality [33]. Setting up a duality with password guessing attacks, O’Gorman [34] argued that sample space of a biometric modality, defined as the valid range of values that can be taken by biometric features, can be used to estimate an upper bound on the individuality of a modality. Accordingly, the effective sample space is measured by the inverse of false matching probability which is then mapped to maximal entropy of a modality under the assumption of uniform distribution of sample values. In line with this thinking, Dass et al. [35] focused on deriving an expression to estimate the probability of a false correspondence between minutiae features of two arbitrary fingerprints. This is realized by modeling the distribution of biometric features and using the resulting models to generate random biometric samples needed to calculate the random correspondence probabilities.

Subsequent approaches to quantifying the amount of information available in different biometric modalities adopted alternative definitions that are more focused on modeling between-user and within-user variability of biometric features.
Below, we provide a brief overview of these approaches, discuss their theoretical underpinnings, and evaluate their applicability to measuring distinguishability offered by the voice biometric.

A. Statistical Modeling

In [27], Daugman proposed a method for measuring uniqueness of iris biometric and evaluated it on a large collection of iris scans. The method is based on a feature representation in which each iris scan is transformed into a 2048-dimensional binary vector by applying a multi-scale wavelet decomposition to iris textures and encoding resulting phase characteristics. The gist of the estimation method relies on comparison of distance based statistics computed from actual user vectors and to those from synthetically generated vectors with elements drawn from a binary distribution in an identically independently distributed (iid) manner. By interpreting the match between each element of two user vectors as a Bernoulli trial, the total number of matches is expressed as a random variable. This essentially corresponds to the Hamming distance between the two vectors which is known to follow binomial distribution under the iid assumption.

The binomial distribution can be characterized by the number of elements $N$, the probability of success in each trial $p$, and the variance of the number of matches $\sigma^2$ as

$$N = p(1 - p)/\sigma^2. \quad (4)$$

Hence, for an empirically obtained distribution, measured mean and variance values (which are estimators for $p$ and $\sigma^2$) can be used to determine the number of iid elements, $N$, in the vector. Using this formulation, Daugman computed normalized Hamming distances between 4258 user vectors in a pair wise manner which yielded more than 9 million comparisons. Then, the resulting mean and variance values are evaluated to determine the corresponding degree of freedom in a binomial distribution, i.e. equivalent $N$ that will yield the same statistic from iid binary vectors, which is found to be 249. Since the iris code is a binary representation, it can be interpreted to have 249 bits of entropy.

This method of estimating uniqueness has certain limitations. The reliability of estimation depends on the underlying dependency of the feature vector array. Our observations show that for apparent forms of dependencies, such as repetition of the elements feature vector, this approach is effective. However for more subtle dependencies, say, XOR'ing the first half of the vector with the second half and appending it to the vector, the measured degrees of freedom increases proportionally. Therefore, the method has a tendency to overestimate the number of independent elements in the vector.

This approach also assumes that each element of the feature vector is equally important as the contribution of each feature to Hamming distance is equally weighted. Hence, it cannot be generalized to representations where features are sorted depending on their importance. In addition, this type of modeling holds only when each element of the feature vector is identically and uniformly distributed. Otherwise, the relation given in Eq. (4) does not hold. But most critically, since this approach relies on evaluating pair-wise differences between feature vectors, it cannot incorporate within-user and between-user variations into its formulation. In this sense, it is more suitable for biometric modalities where within-user variability is very limited.

B. Relative Entropy of Feature Distributions

An alternative biometric information measurement approach is proposed by Adler et al. [36] [20] considering facial images and using a relative entropy based formulation. Relative entropy (also known as Kullback-Leibler divergence) is a non-symmetric measure of the difference between two probability distributions which measures the number of additional bits required to code samples from one distribution when using a code optimized for the other distribution. This approach effectively define biometric information as the decrease in uncertainty about the identity of a person in the presence of a collection of a set of biometric features that represent population characteristics. This uncertainty is expressed in terms of relative entropy as

$$D_{KL}(p||q) = \int_{-\infty}^{\infty} p(x) \log_2 \frac{p(x)}{q(x)} \, dx \quad (5)$$

where $p(x)$ is the within-user feature distribution and $q(x)$ is the between-user feature distribution. By obtaining empirical distributions of PCA-based statistical features of facial images, the average relative entropy between individuals and the population is computed as a measure of information content.

One limitation of this formulation concerns the fact that modelling within-user variability requires estimation of too many parameters (e.g., mean vector and covariance matrix considering a multivariate normal distribution) which becomes highly error prone when there are only a few samples from each user. Further, when actual distributions are not known or are heavy tailed, the estimation becomes less reliable. Aside from these limitations, this approach has a tendency of overestimating the discrimination entropy as relative entropy provides a measure depending on how a user is different from the population, yet, it does not capture the fact that two users can sufficiently be different from the population but might still be very alike.

C. Mutual Entropy of Distance Distributions

Another estimation approach is independently introduced by Takashi et al. [18] and Sutcu et al. [37] to alleviate limitations due to lack of sufficient number of user samples needed for modeling. Both approaches are based on the premise that the level of distinguishability provided by a biometric modality not only depends on the utilized feature representation but also on the deployed matching algorithm used for evaluating similarity or closeness between biometric samples, thereby measuring the average biometric information utilised by the overall system. To incorporate this into its formulation, [37] proposed computing the relative entropy between within-user and between-user distributions of the utilized distance metric rather than using feature distributions directly. Alternatively, [18] provided a mutual information based formulation that
asymptotically approximates relative entropy in order to obtain an upper bound on the entropy of the biometric system. Since these measures rely only on distance distributions, they effectively reduce high-dimensional feature distributions given in Eq. (5) to single dimensional distance distributions. Hence, they do not suffer from difficulties of estimating parameters of multivariate distributions. In addition, within-user variability can be captured more accurately as the number of data points needed for modeling increases in proportion to the square of the available number of samples due to pairwise comparison of user samples. Overall, this resulted with an analytically more tractable approach where the reliability of estimates mainly depend on accuracy of two distributions. The obvious shortcoming of this type of an approach is that it is not a true measure of biometric information content as it also depends on system parameters. However, achievable distinguishability within the confines of a biometric identification system is also a key consideration in practical settings.

D. Applicability of Existing Measures to Voice Biometric

To determine the uniqueness of human voice, limitations and strengths of these measurement approaches must be evaluated in the context of established feature representation for voice. In this regard, an important attribute of i-vectors is that their elements can be assumed independent because the total variability matrix, $T$, involved in their calculation can be regarded as an eigenspace with i-vectors functioning as eigenvectors. This is further confirmed by the covariance matrix of i-vectors being close to diagonal. Another attribute concerns the fact that i-vector elements are sorted based on their ability to distinguish speakers as they are obtained through linear discriminant analysis. Correspondingly, error rates of speaker verification systems do not decrease linearly with decreasing dimensionality of i-vectors. Lastly, elements of i-vectors are continuous valued and are modeled as a Gaussian mixture distribution as part of the GPLDA based matching process.

Considering the overall characteristics of i-vector representation, these measures have some shortcomings with respect to their applicability to assessing uniqueness of human voice. In the case of statistical modeling [21], not only each i-vector element has a different discriminative power but also their quantization will not yield the required uniform distribution. Further, i-vectors have relatively high within-user variability which cannot be adequately captured by this approach. Although the relative entropy based estimation approach [36] [20] does not require quantization of i-vector elements, it must be noted that its formulation is more sensitive to modeling errors. Since computation of Eq. (5) involves division of two distributions, calculations are more prone to errors at distribution tails where values are small and accurate modeling is typically challenging due to limited number of samples per speaker. Moreover, i-vector elements follow a Gaussian mixture model which further increases the number of parameters to be correctly determined. Finally, the mutual entropy based measurement approach utilizing distance distributions between features, [18], [37], crucially estimates the distinguishability provided by a speaker verification system and cannot be generalized to distinguishability intrinsic to actual feature representations.

Inspired by the mutual information based formulation of Takahashi et al. [18], we introduced a new approach for estimating biometric information content of human voice using i-vector representation [38]. Most notably, in this approach, i-vector elements are quantized to obtain a more tangible uniqueness measure defined in terms of number of bits. Further, this measure utilizes actual feature vectors by modeling their distribution, instead of using distribution of the distance between user samples. As a result, the resulting estimate is less dependent on verification system parameters. This study further expands on this initial work to more systematically investigate the effects of i-vector discretization and determines how estimates vary depending on the number of speakers under a more accurate modeling of within-user variability. The details of our approach are discussed in the following section.

IV. Proposed Method

We define biometric information as the ability to uniquely identify speakers through their biometric traits under the realistic assumption that aggregate population characteristics are known. In the case of voice biometric, this reduces to the uncertainty in the composition of a speaker’s i-vectors and can be more formally expressed by the concept of entropy. Given a random variable $S$ representing a randomly selected speaker, among a group of $n$ speakers $\{s_1, \ldots, s_n\}$ and a (discrete) multivariate random variable $I = [I_1, \ldots, I_{200}]$ whose realizations represent individual i-vectors of speakers, the degree of dependence between the two variables provides a measure of intrinsic distinguishability associated with i-vector representation. In fact, the more inter-related the identity of a speaker to his/her i-vectors, the higher is the biometric information content provided by the representation. Similarly, if the two are less dependent, the biometric representation will be less discriminative of the the speaker identity and, thereby, will yield lesser overall information. Hence, the mutual information between $S$ and $I$, can be used to evaluate the biometric information content similar to initially formulated in [18] as,

$$I(S;\mathbf{I}) = H(S) - H(S|\mathbf{I}),$$

where $H(S)$ denotes the entropy of $S$ and $H(S|\mathbf{I})$ is the corresponding conditional entropy expressing the average uncertainty in speaker identities given the population characteristics. Takahashi et al. [18] argued that this quantity asymptotically approximates the relative entropy and used within-speaker and between-speaker distributions of matching scores to evaluate it.

This formulation effectively measures the decrease in uncertainty about the identity of speakers due to known aggregate characteristics. However, there are a number of challenges in evaluating Eq. (6). First, the probability distribution describing the uncertainty of speaker identities is not known as some speakers may have more unique or common i-vectors. In the absence of this distribution, all speakers can be assumed to be equally likely to be identified; thereby, maximizing $H(S)$
and potentially leading to an over-estimation in calculations. Second, the evaluation of conditional entropy, \( H(S|I) \), crucially requires recomputing the distribution of uncertainties concerning speaker identities for a given i-vector, as speakers with i-vectors distributed in that locality of the i-vector space will be better identifiable.

To avoid these complications, in our approach, we utilize the alternative derivation for \( I(S; I) \), expressed as

\[
I(S; I) = H(I) - H(I|S),
\]

where \( H(I) \) corresponds to the entropy of speaker i-vectors and \( H(I|S) \) is the corresponding entropy conditioned on speaker identity, i.e. average entropy in each speaker’s i-vectors. Both of these quantities require estimating the corresponding probability distribution functions which can be empirically obtained when sufficient speaker data is available. Further since this formulation directly utilizes i-vector distributions, instead of relying on matching scores from the verification system, it serves as a more reliable measure of information content.

More critically, the above formulation does not yield to a tangible information measure expressed in bits when evaluated on continuous variables, such as i-vectors whose elements take real values. Therefore, unlike the continuous representations used in speaker verification systems, i-vectors need to be discretized. This, in turn, requires parametrizing the verification system accordingly. For this purpose the UBM and GPLDA parameters must be obtained from quantized speaker i-vectors. Since i-vector elements are uncorrelated, they can be discretized using element-wise scalar quantization rather than through vector quantization. Moreover, the distribution of i-vector elements are highly non-uniform; therefore, minimizing the error (i.e., information loss) due to quantization is critical to retain an accurate representation. This can be realized by using optimal quantization methods, such as Lloyd-Max quantizer, that can better adapt to the distribution of the i-vector elements.

To evaluate Eq. (7) both \( H(I) \) and \( H(I|S) \) must be computed. Since \( I \) can be considered to have 200 independent random components, i.e., \( [I_1, I_2, ..., I_{200}] \), \( H(I) \) can be calculated as the sum of the entropy of each i-vector element as

\[
H(I) = \sum_{j=1}^{200} H(I_j) = H(I_1) + \ldots + H(I_{200}).
\]

Similarly, the conditional entropy \( H(I|S) \) can be calculated by taking an average over all speakers in the dataset as

\[
H(I|S) = \frac{1}{n} \sum_{i=1}^{n} P(s_i) H(I|S = s_i)
\]

where \( P(s_i) \) is the probability of encountering speaker \( s_i \) among \( n \) speakers wherein each speaker can be considered equally likely, i.e., \( P(s_i) = \frac{1}{n} \), and \( H(I|S = s_i) \) is the entropy in speaker \( s_i \)’s i-vectors. Hence, by substituting Eqs. (8) and (9) in Eq. (7), the uniqueness provided by the i-vector representation can be finally calculated as

\[
I(S; I) = \sum_{j=1}^{200} H(I_j) - \frac{1}{n} \sum_{i=1}^{n} \sum_{j=1}^{200} H(I_j|S = s_i). \tag{10}
\]

Obviously, evaluating this expression reliably requires both a large number of speakers and large number of speech samples per speaker. We next describe the datasets used in our measurements along with details concerning their creation.

V. DATASETS

Reliable estimation of uniqueness ultimately comes down to whether the data used for modeling speakers accurately capture between- and within-speaker variations. Several speech corpora have been used for benchmarking the performance of speaker verification methods. However, when considered in the context of quantifying individuality of a representation, these datasets suffer from limitations that restrict their applicability.

Most critically, the number of speakers in those datasets is rather low, varying from several hundreds up to a thousand, and typical duration of speech samples from each speaker does not provide adequate data points needed for accurate evaluation of Eq. (10). Moreover, speech utterances included in these datasets don’t sufficiently exhibit the natural variation present in a speaker’s voice as they are captured under well defined settings.

To address these limitations, in this work, we created two custom datasets by essentially collecting speech samples from public sources. Although a speech corpus drawn entirely from public data sources does not provide a control over how samples are recorded, it allows creating a large-scale and diverse dataset as needed by our formulation. Following subsections provide details on how these datasets are generated

A. TEDx Dataset

In our earlier work \[38\], we performed measurements on a corpus obtained from TED Talks which involves a library of videos wherein speakers deliver monologue style presentations on a wide variety of topics. Although the online archive for TED Talks provides rich metadata about the talks and speakers, the audio captions, and the option to chose among a variety of high quality audio recordings, the available number of videos is limited to only a few thousand. To create a more diverse dataset, in this work, we utilised TEDx Talks which follows a similar format and the same rules as the original TED Talks. Since TEDx events are organized independently, its archive involves much larger collection of talks in a variety of languages \[40\].

TEDx videos are featured on the TEDx channel of YouTube video sharing website. The durations of these videos range from a few minutes to up to an hour, with most talks lasting

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1 The widely used NIST SRE 2004-2010 dataset includes 976 speakers with more than 40 seconds of speech samples per speaker \[16\], the TIMIT dataset has 630 speakers and around 30 seconds samples from each speaker \[39\]; and the YOHO dataset involves 138 speakers with around 3 minute long samples from speakers \[15\].

2 Both of the newly created datasets will be made publicly available following final modifications of this manuscript.
around 20 minutes. Although it is not possible to ascertain recording conditions for these talks, a great majority of them is determined to have an audio bitrate around 120 Kbps, which is most likely due to YouTube re-encoding of all uploaded videos. To create our dataset comprising speech samples of TEDx speakers, we first obtained URLs of all videos by going through all available TEDx playlists. We then examined the index page of each video by searching video metadata for the content tag in order to identify the talks in English language. We disregarded all videos that lacks a caption file and identified 24,500 videos whose audio tracks, as well as the audio captions, were downloaded using the youtube-ld download tool [41].

The TEDx presentations are given by a single speaker; therefore, speech overlap from multiple speakers is not a concern. However, obtaining speech samples from each speaker further requires eliminating all non-speech and non-distinguishable utterances from the obtained audio tracks. To realize this, we utilized the audio captions associated with each video. For our analysis, we used the CMU Sphinx Aligner Toolbox [42], which aligns an audio input with its transcript, to identify the time interval when each word in the caption is spoken in the source audio. Essentially, this enabled us to remove all non-speech utterances like music, applause and silence from audio samples, as well as all speech utterances where background noise masked their audibility.

Using this tool, we determined that total processing time spent during alignment of each audio track is proportional to the overall length of audio track. However, the tool would occasionally take too long to produce a result or would fail to return results because of an error. Therefore, we eliminated all tracks whose processing took more than twice the duration of the input audio track, leaving us 22,598 tracks. Then, all speech utterances aligned with caption words are subjected to voice activity detection [43] to eliminate silence intervals between utterances. Resulting speech segments are then combined together to obtain a speech-only audio sample from each audio track as depicted in Fig. 1. The processing of audio tracks was performed on three workstations, with Intel Core i7 CPU and 32 GB RAM, over a time period of five months. From the resulting speech samples, we eliminated all those that don’t allow extraction of a single i-vector (i.e., requiring 5 seconds of speech utterance). This overall led to a collection of varying length speech samples associated with 20,741 speakers, which is an order of magnitude larger than existing voice corpora.

Fig. 1. Steps for extracting a speech samples from TEDx Talks videos.

B. Movie Dialogues Dataset

Similar to various other datasets, the TEDx dataset involves speech samples expressed in a limited emotional tone of voice (i.e., dominated by presentation voice) and does not incorporate the emotional range intrinsic to a speaker’s voice. It is well known that emotions are reflected in the voice tone of a speaker [44], [45], [46]. Hence, an attempt to measure the uniqueness of human voice solely using such a corpus will undoubtedly result in overestimation. To partially address this challenge, we created another dataset comprising speech samples extracted from movies. Since movies are typically composed of dialogues between two or more speakers made under various circumstances, they provide a better basis for capturing the within-speaker variability.

Therefore a similar approach based on alignment of audio with the movie caption is deployed to obtain speech samples. The main challenge here, however, concerns correct attribution of each speech utterance with its speaker. Although movie subtitles follow some style, they don’t necessarily identify speakers individually in the text-dialog. Most generally markers, such as hyphens, are used to denote dialogues without including speakers’ names. Even when identifiers are used, they may be excluded if the speaker is visually apparent in the corresponding time-synchronized video frames. Furthermore, descriptions for non-verbal sounds may also be included as part of subtitling. Therefore, before an alignment is performed, the speech segments associated with each speaker must be determined. One way to realize this is through clustering of utterances based on a speaker verification approach. That is, creating a model for each speaker and then verifying the source of each utterance. However, automatic creation of speaker models is error prone as it must be done incrementally, especially for actors with fewer lines of dialogue. Therefore, we considered utilizing movie scripts, which are written versions of what happens in a movie, in conjunction with movie subtitles to correctly attribute each part of a dialogue to a speaker.

For this purpose, we determined public sources on the Web that archive movie scripts and screenplay3. Examining these collections, we identified more than a thousand movies to extract dialogue samples. We then retrieved these scripts and manually eliminated those that were in scanned document format and those that do not explicitly designate the speaker for each speech segment. In addition, movie soundtracks are extracted from their DVD formatted versions using FFmpeg video processing tool along with their subtitles. The retrieved scripts are then checked against actual dialogues of soundtracks for potential discrepancies. The comparison of subtitles and the movie scripts of several movies revealed further differences both at the narrative-level, due to missing or extra lines, and at the sentence-level, where similar meaning was conveyed with a different sentence construction or choice of words. We determined that these differences were essentially due to scripts being draft versions and not the final shooting scripts.

All styles of subtitling utilize line-breaks to segment speech, 3We identified following websites as potential sources for movie scripts with the first one identified to provide the most comprehensive collection. http://www.imdb.com/all%20scripts/ http://www.dailyscript.com/movie.html http://www.simpllyscripts.com/movie-screenplays.html http://www.awesomefilm.com.
and when multiple speakers are present in a scene they are separated by breaks. Therefore when attributing speech segments, each text-line or full-sentence (when punctuation is used) in the subtitles are used as the basis of search. Since smaller phrases are likely to yield various matches in the script, we initially identified all uniquely matching lines and sentences in the script along with their speakers. Then, treating those exact matches as reference points subsequent text segments in the script are searched only within a limited range in subtitles, thereby restricting probability of false attributions. Each of the remaining lines in the movie subtitle is then attributed to a speaker by evaluating its similarity to text in the script [47].

When computing the similarity of two strings, each text-line in subtitle is matched against text-strings that may be shorter or longer by two words. For this purpose, we first performed a string comparison using Levenshtein distance measure. We empirically determined similarity thresholds of %85 or above in order to accept a match and %40 or below to eliminate a line from matching. Remaining unattributed lines are subjected for further comparison. To overcome potential spelling errors, we first utilized the Jaro-Winkler distance measure to compare words in the subtitles and the script, and two words with comparison values more than %95 are considered to be the same. Among the remaining lines for which string search yielded a Jaccard similarity above %50 are considered matched and attributed to the corresponding speaker.

After attributing speech segments in the subtitle to speakers denoted in the movie script, we used Sphinx tool to align text with audio just as before to identify each utterance corresponding to spoken words in the subtitle. Finally, we utilized the IMDB cast lists to identify actors corresponding to speakers in each movie and to consolidate speech samples of actors obtained from different movies. The steps for the overall process is shown in Fig. 2. At the end of this overall process, we were able to obtain speech samples of 1595 actors from 249 movies. Noting that we extracted each i-vector from 5 seconds long speech samples, our movie dialogues dataset included 556 actors with at least 10 i-vectors, 286 actors with more than 20 i-vectors and 132 actors with more than 40 i-vectors.

We must note here that our movie dialogues datasets resulted with fewer speakers than expected due to two main factors. First is due to the inability to access final versions of movie scripts which would have matched exactly with the movie subtitles and enabled us to attribute each utterance to its speaker. Hence to prevent false-attributions as much as possible, our association method was essentially tuned to eliminate text-lines if there is ambiguity when evaluating similarity within draft scripts. The second factor is due to performance of the aligner which performed considerably worse on movies as compared to TEDx videos due to higher interference from background noise, sound effects, and simultaneous dialogues. Nevertheless, this dataset is unique in its composition and its attempt to capture true within-speaker variability in human voice.

VI. RESULTS

To extract i-vectors from speech samples in both datasets, we used the MSR Identity Toolbox [48]. For analysis, the speech-only audio obtained from each video is initially divided into samples of 5 seconds-long segments. The MFCC features are computed using a 25 milliseconds sliding Hamming window at intervals of 10 milliseconds. In addition to 19 MFCCs extracted from each frame, the log energy as well as delta and acceleration coefficients (first and second order derivatives computed over time) are also obtained as features. The resulting 60 dimensional expanded MFCC features calculated from each segment are then modeled with a 512-component GMM, and the total variability matrix is estimated by five iterations of the expectation-maximization (EM) algorithm. The resulting high-dimensional i-vector representation is then reduced to a 200 dimensional vector through LDA as noted earlier. The GPLDA model used in computing verification scores for i-vectors is estimated by 10 iterations of EM algorithm while preserving the i-vector dimensions.

The UBM used in computation of i-vectors is obtained using speech samples of 5 thousand speakers out of the 20,741 speakers in the TEDx dataset. Use of a diverse set of speakers ensured speaker independence in the background model generation while still leaving many speakers to obtain reliable uniqueness estimates. Also, to better quantify the impact of number of available i-vectors on measurements, speakers with fewer speech samples are primarily used for building the UBM. Overall, the UBM is generated using 10 speech samples from 4,610 speakers and 1-9 samples, depending on availability, from the remaining 390 speakers, with an overall average of 9.6 samples per speaker.

A. Quantization of I-Vectors

Our uniqueness estimation method, described in Sec [14] assumes discrete variables; therefore, continuous valued i-vectors must first be quantized. Since quantization operation incurs information loss, it is expected to cause a decrease in the individuality inherent to i-vectors. However, at the same time, it is very plausible that the i-vector based speaker verification and identification systems do not strictly depend on a continuous representation of i-vectors in their performance. Therefore, it is important to determine the right level of quantization that can be performed while ensuring a comparable performance when operating on continuous and discrete i-vectors.

To quantify the impact of quantization, we utilize the speaker verification performance as the basis of evaluation. That is, by applying different amounts of quantization to i-vectors, we determined how achievable error performance changes with respect to the use of original i-vectors. For this
purpose, all speech samples are divided into three groups. The first group includes samples associated with 5 thousand speakers set aside to train the UBM. The second group of samples are used to create speaker models for each of the remaining 15,741 speakers and all but one of speaker samples are used for this goal. This group includes an average of 100.23 samples from each speaker, and each speaker model is created using two approaches [48]. In the first one, i-vectors extracted from all samples are averaged together to obtain one speaker i-vector. In the second one, MFCC features are averaged across multiple samples of a speaker and an i-vector is extracted from these averaged MFCC features. Finally, the third group includes 15,741 samples, with one randomly selected sample from each speaker (not used during creation of speaker models) to be used for testing. The speaker models and test samples are used to determine thresholds needed for verifying the speaker of i-vector, which can be translated into a 15,741 × 15,741 matrix of decision scores to compute the false-acceptance and false-rejection rates in speaker verification.

As the first step, we examined i-vectors designated for building the UBM in order to learn their distribution and determine the best suited quantization scheme. Since i-vector elements are uncorrelated there is less to be gained from vector quantization. In addition, the distribution of i-vector elements is highly non-uniform; therefore, we utilized the Lloyd-Max algorithm to create an optimal partitioning (in the mean-squared error sense) of the i-vector elements for a given number of quantization levels (i.e., bits per quantized sample). All i-vectors are then quantized using the learned parameters for each quantization setting. The GPLDA model is generated based on quantized speaker i-vectors used in generation of the UBM just as it is done with original i-vectors. Speaker models are similarly generated using both averaging approaches, and the speaker of quantized i-vectors in the test group are verified using the newly generated GPLDA model.

We use the equal error rate (EER) as the performance metric for speaker verification, which refers to the point where false-acceptance and false-rejection rates are equal. The EER values obtained under different quantization settings are given in Table I. In the table, second column shows EER values achievable when original, non-quantized i-vectors are used and subsequent columns correspond to increasing number of quantization bits. The two error values, EER1 and EER2, respectively correspond to cases where i-vectors and MFCC features are averaged when creating speaker models. As the values in the second and third rows indicate, when i-vector values are quantized to low levels of bit resolution (i.e., 1 or 2 bits), EER values are higher than the continuous case. This is expected as severe quantization suppressed both between-speaker and within-speaker variability in i-vectors, making them less distinguishable. As expected, at higher quantization bit levels, EER values approaches to non-quantized case.

For quantization levels in between the two extremes, however, we observed an interesting phenomenon where quantization of i-vectors yielded a slightly improved EER than the continuous case. This essentially indicates that at 2-4 bits non-uniform quantization of i-vector elements, the gain obtained due to decrease in within-speaker variability compensates for the errors due to decrease in between-speaker variability. In other words, quantization enabled better clustering of speaker i-vectors while still preserving relative distances between different speakers. We determined that another factor contributing to this effect is the use of n-bit codewords to represent quantized i-vector elements (where n is determined based on number of quantization levels) instead of using actual quanta values associated with each quantization interval. Our comparison of the two cases revealed that codeword based representation yields lower within-speaker variance in the GPLDA which in turn found to cause, on average, 8% decrease in measured EER values.

We must note that this observation is in agreement with results of our earlier work [38] as given in the third row of the same table. This work utilized a collection of speech samples obtained from TED Talk videos of 1,914 speakers in a similar manner. These videos feature higher quality audio recordings as well as very accurate transcriptions. The EER values obtained on this dataset, where speech samples of 993 speakers are used for UBM generation and samples of 921 speakers are used for measurements, also exhibited the same behavior. On this dataset, however, when the number of quantization bits increased from 4 to 5 bits, the corresponding EER value did not change. This can be mainly attributed to limited number of speakers used in testing and generation of the UBM, which makes EER computations less accurate.

Based on these results, uniqueness estimates will be evaluated considering 2-3 bit quantization of i-vector elements, depending on how speaker models are generated, as it yields comparable or better EER results as the original, continuous valued i-vectors.

| # of bits | 1 | 2 | 3 | 4 | 5 |
|-----------|---|---|---|---|---|
| EER1      | 2.73 | 2.46 | 2.56 | 2.66 | 2.81 |
| EER2      | 2.39 | 2.36 | 2.38 | 2.43 | 2.45 |

B. Uniqueness Estimates From TEDx Dataset

After discretization of i-vectors into a fixed number of quantization levels, we estimate the uniqueness in human voice using i-vectors of 15,741 speakers in the TEDx dataset as described in Sec. IV. This is realized by computing the entropy of overall i-vectors, H(I), and the entropy in a speaker’s i-vectors, H(I|S), to finally obtain the biometric information content of i-vector representation, I(S;I), as defined in Eqs. (7)-(10). Table II provides calculated values for all terms considering increasing number of quantization levels, 2, 4, 8, 16, and 32, where each quantized i-vector element is described by 1 – 5 bits. As it can be seen in these results estimates start from 28 bits for 2-bit quantization and gradually increases to 89 bits for 5-bit quantization setting. This increase in the uniqueness estimates, however, does not translate into better discrimination of speakers. As demonstrated in the results
of Table I in terms of the achievable EER performing 3-bit quantization yields the same level of distinguishability as using the original i-vectors. That is, using a finer (higher resolution) representation of an i-vector does not lead to a discernible improvement in identification but rather contributes to randomness in i-vectors. Overall, measurements performed on TEDx dataset estimate the uniqueness of human voice to be in the range of 45 to 57 bits depending on the number of bits used to represent each i-vector element, as suggested by findings of Table I.

Next, we examine in more detail the impact of between-speaker and within-speaker variability on obtained estimates. Capturing between-speaker variability essentially requires uniform sampling of i-vector space. This can be roughly achieved by using voice samples of large number of randomly selected speakers. Table III provides estimates for increasing number of speakers when the number of samples for each speaker is fixed at 80, which sums up to 7 minutes of pure speech. These results overall show that estimates based on fewer speakers (10-30) result with a significant underestimation as distribution of i-vectors cannot be reliably obtained and $H(\mathbf{I})$ is miscalculated. At the other extreme, we observe that increasing the number of speakers by an order of magnitude, from one to ten thousand, the estimates change only marginally. Thus, it seems having a dataset of thousand speakers will yield reasonably accurate estimates as long as sufficient number of samples per speaker are present. The table also incorporates the estimates obtained from the TED dataset in its last column for comparison, which includes around a thousand speakers with 71 samples per speaker on average [38]. Comparing the estimates obtained using the two datasets around the same number of speakers, a 1-4 bit difference is observed depending on the number of quantization bits. We believe this difference is potentially due to the fact that TED dataset includes more high quality speech samples than the TEDx dataset.

Within-speaker variability is the other main factor that contributes to the accuracy of estimates. This is essentially determined by the number and diversity of speech samples used for creating each speaker’s model. Table IV shows how capturing within-speaker variability, in terms of the number of samples per speaker, affects estimates. The first two rows of the table show the number of samples per speaker used for creating speaker models and the number of speakers with that many samples. It can be seen here that estimates based on 10 samples are roughly 1.5-4 times higher than those obtained using 90-100 samples. More importantly, we observe that estimates converge closely only if a large number of samples (around 100) are used. By combining these results, we can further improve our uniqueness estimate of human voice to 43-52 bits based on speech samples of 1363 speakers with 140 samples each.

These results indicate the necessity for a large number of samples; however, they don’t sufficiently reflect the effect of emotions on the voice as the samples comprising the TEDx dataset are mainly limited to emotional tones defined around a presentation setting.

### Table II

| bits | $H(\mathbf{I})$ | $H(\mathbf{I}|S)$ | $I(S;\mathbf{I})$ |
|------|-----------------|--------------------|------------------|
| 1    | 199.13          | 171.50             | 27.63            |
| 2    | 368.86          | 324.03             | 44.82            |
| 3    | 544.51          | 487.70             | 56.80            |
| 4    | 727.29          | 657.55             | 69.74            |
| 5    | 898.00          | 808.99             | 89.01            |

### C. Uniqueness Estimates from Movie Dialogues

The Movie Dialogues dataset contains relatively small number of speakers and speech samples as compared to TEDx dataset, but it provides a more diverse kind of voices and utterances. Hence, using the earlier generated UBM, we performed the same analysis on this dataset. Table V presents corresponding results when speaker models are generated from varying number of samples. It is immediately obvious that resulting uniqueness estimates are significantly lower than those found in Tables III and IV. This difference may partly be attributed to real-life and uncontrolled conditions of audio acquisition in movies; however, the quality of samples cannot be a significant factor in this as, ultimately, speech samples only include spoken words that could be matched to the subtitle. The major factor in play here is the increased within-speaker variability which induces ambiguity in the estimated speaker models. This is also supported by earlier observation that application of audio effects on voice samples (such as changing loudness, shifting pitch, addition of background noise and echo) causes a somewhat similar reduction in estimates, though to a lesser extent [38].

Overall, as the number of speakers with large number of samples are limited, uniqueness estimate can be made in conjunction with results of Tables III and IV. As the results of Table III demonstrate, estimates of uniqueness based on fewer speakers (30 or less) leads to an underestimation. Therefore, estimates in the last three columns of Table V can be interpreted as lower bounds. That is, at 2 and 3 bits quantization, estimates should be higher than 12 and 18 bits, respectively. At the same time, results of Table V indicate that using fewer speaker samples (10-30 samples per speaker) overestimates the inherent uniqueness. Hence, estimates should be expected to be lower than 18 and 31 bits, respectively, for 2 and 3 bit quantization. Therefore, based on measurements obtained using speech samples of 64-46 speakers with 60-70 samples per speaker, we estimate the uniqueness of human voice to be around 13-20 bits, depending on the number of quantization levels, when emotional variability is taken into account.

### D. Comparison with Other Measures

We also compared uniqueness estimates obtained through our mutual information based measure with those generated using the relative entropy and statistical modeling based measures on TEDx dataset as presented in Table VI. To determine the degree of uniqueness with respect to the measure introduced by Daugman [21], which evaluates statistics of Hamming distance distribution of pairwise differences of feature

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TABLE II

| Uniqueness Estimates for TEDx Dataset with Increasing Number of Quantization Bits |
|-----------------------------------|-----------------|--------------------|------------------|
| bits | $H(\mathbf{I})$ | $H(\mathbf{I}|S)$ | $I(S;\mathbf{I})$ |
|------|-----------------|--------------------|------------------|
| 1    | 199.13          | 171.50             | 27.63            |
| 2    | 368.86          | 324.03             | 44.82            |
| 3    | 544.51          | 487.70             | 56.80            |
| 4    | 727.29          | 657.55             | 69.74            |
| 5    | 898.00          | 808.99             | 89.01            |
TABLE III  
UNIQUENESS ESTIMATES FROM TEDX DATASET FOR VARYING NUMBER OF SPEAKERS (80 SAMPLES/SPEAKER)

| # of speakers | TEDx Dataset | TED dataset [38] |
|---------------|--------------|------------------|
|               | bits | 10  | 30  | 100 | 300 | 1000 | 3000 | 10000 | 921 |
| 1             |     | 24.33 | 27.30 | 27.94 | 27.93 | 28.04 | 28.03 | 27.87 |     |
| 2             |     | 38.74 | 44.15 | 45.62 | 45.66 | 45.76 | 45.75 | 45.50 | 46.94 |
| 3             |     | 49.53 | 56.55 | 58.50 | 58.62 | 58.73 | 58.72 | 58.41 | 62.33 |
| 4             |     | 62.08 | 70.49 | 72.95 | 73.21 | 73.36 | 73.36 | 73.02 | 80.41 |
| 5             |     | 81.41 | 91.52 | 94.74 | 95.22 | 95.46 | 95.49 | 95.16 | 100.49 |

TABLE IV  
UNIQUENESS ESTIMATES FROM TEDX DATASET FOR INCREASING NUMBER OF SAMPLES

| Number-of-samples/speaker (Total speakers) | bits |
|--------------------------------------------|------|
|                                            | 10   | 20   | 30   | 40   | 50   | 60   | 70   | 80   | 90   | 100  |
| 87.78                                      | 42.90| 34.52| 31.67| 30.22| 29.34| 28.71| 28.23| 27.87| 27.58| 27.32|
| 85.91                                      | 87.78| 64.18| 56.01| 51.90| 49.42| 47.71| 46.44| 45.49| 44.74| 44.09|
| 142.67                                     | 142.67| 96.42| 80.03| 71.63| 66.50| 62.98| 60.37| 58.41| 56.85| 55.56|
| 225.51                                     | 225.51| 144.74| 113.96| 97.97| 88.20| 81.55| 76.68| 73.02| 70.12| 67.74|
| 332.24                                     | 332.24| 216.51| 166.78| 139.37| 122.15| 110.33| 101.69| 95.15| 89.99| 85.79|

TABLE V  
UNIQUENESS ESTIMATES FROM MOVIE DIALOGUES DATASET FOR INCREASING NUMBER OF SAMPLES

| Number-of-samples/speaker (Total speakers) | bits |
|--------------------------------------------|------|
|                                            | 10   | 20   | 30   | 40   | 50   | 60   | 70   | 80   | 90   | 100  |
| 556                                        | 14.66| 10.48| 8.95 | 8.08 | 7.53 | 7.26 | 7.00 | 6.77 | 6.78 | 6.92 |
| 286                                        | 34.62| 22.38| 17.94| 15.90| 14.52| 13.59| 12.88| 12.13| 12.30|     |
| 184                                        | 64.45| 40.20| 31.19| 27.03| 24.03| 21.78| 20.05| 18.62| 18.09| 17.88|
| 132                                        | 113.56| 69.40| 52.56| 44.77| 39.13| 34.90| 31.45| 28.60| 27.28| 26.41|
| 64                                         | 184.27| 116.28| 88.12| 74.49| 64.59| 56.60| 50.43| 45.25| 42.45| 40.50|

vectors, we applied it to binary quantized, 200-dimensional i-vectors and measured an entropy of 186.87 bits. This result is in line with the interpretation that this measure estimates the number of independent components in the biometric feature vector.

Similarly for the relative entropy based measure, we performed all steps described by Adler et al. in [20] to original, unquantized i-vectors obtained using speech samples of 11,524 speakers, with 80 samples per speaker. Accordingly, the relative entropy of i-vector distribution is determined to be 80.61 bits. As compared to values obtained on the TED dataset [38], resulting estimates for both measures are found to be 10-30 bits lower. This can essentially be explained by the more comprehensive nature of TEDx dataset, which allows better incorporation of between-speaker variability due to an order of magnitude increase in the number of speakers.

TABLE VI  
COMPARISONS OF MEASURES FOR UNIQUENESS ESTIMATION

| TEDx Dataset | TED Dataset [38] |
|--------------|------------------|
| 186.87       | 195.08           |
| 80.61        | 109.34           |
| 44.82        | 46.94            |
| 56.80        | 62.33            |

VII. DISCUSSION AND CONCLUSIONS

In this work, we seek to estimate the uniqueness of human voice with respect to widely used i-vector representation of voice by speaker recognition systems. For this purpose, we introduced an entropy based measure for uniqueness estimation and used two custom datasets that emphasize the between-speaker and within-speaker variability aspects of voice. These datasets include speech samples collected from public sources such as TEDx Talks video archive and audio tracks of movies, and they are the largest of their kind used in such a study. Our results show that estimates obtained using limited number of speakers and/or samples per speaker may result with significant deviation in the estimated values. Findings also indicate that within-speaker variability is a more important factor affecting the reliability of estimates.

An important implication of our study concerns voice authentication solutions that are increasingly used for access control with the assumption that voice models are unique. As the capability to synthesize speech with a target speaker’s voice improves, the threat landscape for such systems is also evolving. Although high quality voice synthesis requires large amount of data, an attacker may utilize a dictionary of voices with sufficient speech samples (collected from open sources as we did) to identify a voice very similar to particular speaker’s voice and perform synthesis on dictionary data. Our results
show that when several emotional factors that influence a voice are taken into account, estimated uniqueness of human voice will be low and the size of such a dictionary will be in the order of a few thousand to a million speakers (13-20 bits), essentially making such an attack feasible. In contrast, if speakers are confined to circumstances that limit the variation on their voice, the size of the dictionary will be quite high (in the order of $2^{43}-2^{52}$ speakers), limiting the possibility of launching this type of an attack at scale.

Finally, a long-term goal of this work is to help build a systematic approach to estimate the uniqueness of biometric traits, including those biometric like characteristics associated with devices. Several measures have already been proposed towards this goal as covered in Section III. When evaluated together, it becomes evident that quantifying the uniqueness of a modality depends on identifying a measure that matches with characteristics of the underlying biometric feature representation. More critically, our results indicate that claims of uniqueness made based on observations limited in both the number of sources and data points from each source may be highly misleading. Overall, there is still a need for a research effort in introducing new uniqueness measures and consolidating existing ones to ultimately create an overarching framework that can help decide the best measure and the amount of needed data samples when determining the degree of individuality inherent to an observed characteristic.

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