



Multi-channel speaker verification based on total variability modelling

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Abstract

In this work we address the speaker verification task in domestic environments, monitored by multiple distributed microphones. In particular, we focus on the problem of mismatch in the propagation channel between the enrolment stage, which occurs at a fixed position, and the test phase which could happen in any location of a multi-room apartment. Building upon the Total Variability framework and cosine distance scoring, we present two multi-channel solutions: one based on multi-condition training and the other based on several channel-dependent systems. An experimental analysis on a multi-channel multi-room reverberant data-set shows that the proposed solutions are robust against changes in the speaker position and orientation and improve the performance of the single-channel matched baselines.

Index Terms: distant speaker verification, multi-channel, total variability modeling, i-vectors

1. Introduction

One of the most typical problems of domestic scenarios regarding automatic speech processing methods, and particularly speaker recognition systems, is the fact that users can give commands from any position of any room. Consequently, a mismatch is often present between the enrolment and test phases, resulting in a noticeable decrease in the verification performance [1]. In practice, creating suitable speaker models able to cope with any spatial condition is a fundamental challenge for speaker recognition in real-world home automation applications. One possibility to partially tackle this problem would consist in adopting a network of multiple distributed microphones that continuously monitors the target environment. Previous works have reported the advantages of exploring the information from multiple channels. The most common strategy relies on implementing speech enhancement techniques based on multi-channel processing to reduce the amount of reverberation and noise in the speech signals before the identification step [2, 3, 4, 5, 6, 7]. The majority of these techniques (e.g. beamforming, spectral subtraction, etc.) require the availability of a compact microphone array. The latter constraint is relaxed in [8] where a post-processing fusion of independent classifiers, applied to each channel, is presented. On the other hand, the investigation of multi-channel solutions in the Total Variability (TV) framework [9, 10] is still in a preliminary stage. In [11, 12] solutions to improve robustness against condition mismatch (i.e. telephone and distant microphones) are pre-

sented, without considering multiple simultaneous recording of the same utterance. Recently, multi-condition training [13, 14] and an extended version of Probabilistic Linear Discriminant Analysis (PLDA) [15, 16] have been adopted in multi-channel recordings to improve the verification performance.

In this work, we aim at building a position independent speaker verification (SPKV) solution based on the so-called i-vectors [9, 10]: a technique that has rapidly emerged as a powerful approach for SPKV and has become the current de-facto standard. In this factor analysis approach, the speaker and channel variability of a high dimensional GMM supervector are jointly modelled as a single low-rank total-variability space. Then, low-dimensional TV factors are extracted from each speech segment to form a vector, called i-vector, which represents the speech segment in a compact and efficient way. By taking advantage of the multiple microphones distributed in an apartment, we investigate two solutions where either multiple channel-dependent T-matrices or a single combined system are trained and used to obtain multiple target models and test vectors. Suitable combination strategies are then applied to improve the performance of baseline single-channel methods in matched and mismatched conditions. In particular, we assume that the speaker enrolment takes place in a specific spot in the apartment, while verification can take place at any position.

The paper is organized as follows: Sec. 2 introduces the proposed multi-channel total variability solutions, Sec. 3 reports the experimental results on a multi-channel multi-room data-set created on purpose, while Sec. 4 concludes the paper with final remarks and future work.

2. Multi-channel Total Variability

Let us denote with $x_n(t)$ the signal acquired by the n -th microphone ($n = 1, \dots, N$). We consider N single-channel systems and denote their parameters as $\Lambda^n = \{\mathbf{U}^n, \mathbf{T}^n\}$, where \mathbf{U}^n is the channel-dependent Universal Background Model (UBM) and \mathbf{T}^n is the TV matrix. The superscript $\{\cdot\}^n$ denotes the n -th channel-dependent system, trained independently on the data acquired by the n -th microphone. In this way, each SPKV system models information about the specific propagation channel $h_{e \rightarrow n}$ between the enrolment position e and the n -th channel. During enrolment, the signals $x_n(t)$ are used together with the system Λ^n to obtain N speaker model vectors $w_n^n(s)$ for each target speaker s . The subscript $\{\cdot\}_n$ denotes the n -th channel data used in i-vector computation. Likewise, during test, an i-vector $w_n^n(u)$ of the test utterance u is obtained for each channel. Then, a single-channel verification score for each trial is obtained for each system Λ^n based on cosine scoring:

$$C_n^n(s, u) = \langle w_n^n(s), w_n^n(u) \rangle \quad (1)$$

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We considered two i-vector processing stages that are expected to contribute to a partial reduction of the channel variability: i-vector centering and whitening [17]. Both mean and decorrelation matrix parameters are estimated using non-target speaker training data from all the available channels. In addition, T-norm score normalization (only mean) was applied [18], in which the mean off-set is estimated on all speaker target model scores S as follows:

$$C_n^{n'}(s, u) = C_n^n(s, u) - \frac{1}{S} \sum_{i=1}^S [C_n^n(i, u)] \quad (2)$$

This normalization is expected to be particularly beneficial in the closed-set speaker scenario addressed in this work, since for a fixed test segment it will very likely favour the acceptance of at least one trial. Similarly, the centering and whitening trained on multiple channels are expected to reduce the impact of the enrolment mismatch.

2.1. Combined channel-independent T-matrix

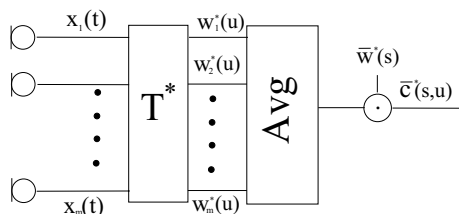


Figure 1: Block diagram of the combined approach.

During the verification stage, since the speaker position generally differs from the enrolment one, the propagation channel $h_{u \rightarrow n}$ between the test speaker position and the n -th microphone is no longer captured by Λ^n . Thus, the vector $w_n^n(u)$ is not necessarily the one that better models the test propagation channel. This mismatch typically results in a performance degradation. To mitigate this effect, following the multi-condition strategy presented in [13], we consider a channel independent system $\Lambda^* = \{\mathbf{U}^*, \mathbf{T}^*\}$, trained using the data acquired by all the microphones. This way we jointly model the different possible propagation channels $h_{e \rightarrow n}$ for $n = 1, \dots, N$, and obtain a system robust to changes in the propagation channel. During the enrolment stage, N target speaker vectors $w_n^*(s)$, one for each channel, are obtained using Λ^* . Since the i-vectors have been extracted using the same Λ^* system, we can derive a channel-independent i-vector by taking the average:

$$\bar{w}^*(s) = \frac{1}{N} \sum_{n=1}^N w_n^*(s). \quad (3)$$

In the test stage, for each test utterance u we extract an i-vector $w_m^*(u)$ for each channel m , $m = 1, \dots, M$, where M is the number of microphones in the room and typically $M \neq N$. Given $\bar{w}^*(s)$ and $w_m^*(u)$ we can obtain M different speaker verification scores per trial:

$$C_m^*(s, u) = \langle \bar{w}^*(s), w_m^*(u) \rangle \quad (4)$$

However, we can obtain a better estimation of the test utterance

by computing the average of the M test i-vectors:

$$\bar{w}^*(u) = \frac{1}{M} \sum_{m=1}^M w_m^*(u) \quad (5)$$

At this point a single verification score can be obtained applying the cosine scoring on the average target and test i-vectors:

$$\bar{C}^*(s, u) = \langle \bar{w}^*(s), \bar{w}^*(u) \rangle. \quad (6)$$

Figure 1 shows a summary diagram of the method described in this section.

2.2. Distributed channel-dependent T-matrix

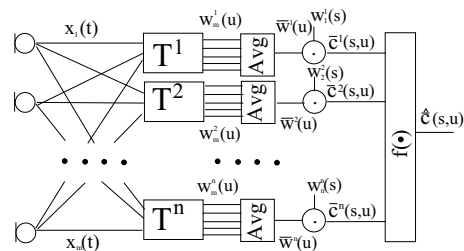


Figure 2: Block diagram of the distributed solution.

As an alternative to the combined approach, we consider a distributed multi-channel solution based on the N channel-dependent systems Λ^n . Each system Λ^n is used to extract a different i-vector for each recording m of the test utterance u , resulting in $N \times M$ test i-vectors $w_m^n(u)$. In this case $m = 1, \dots, M$ is the channel acquiring the signal $x_m(t)$, while n identifies the system Λ^n used to extract the i-vector. The underlying idea is that we expect that some of the $N \times M$ system-channel combinations might be more similar to one of the N enrolment conditions. In other words, we believe that for any test position there may be a microphone for which the characteristics of the corresponding propagation channel will be approximately modelled by one of the enrolment propagation channels $h_{e \rightarrow m}$. Combining all microphone signals with all the matrices \mathbf{T}^n results in $N \times M$ possible verification scores for a given target speaker s and a test utterance u :

$$C_m^n(s, u) = \langle w_n^n(s), w_m^n(u) \rangle \quad (7)$$

Given this multi-channel framework, first we attempt to obtain better estimations of test i-vector by averaging those vectors extracted from the M channels using the same system Λ^n :

$$\bar{w}^n(u) = \frac{1}{M} \sum_{m=1}^M w_m^n(u) \quad (8)$$

The $\bar{w}^n(u)$ average test i-vector is then used to obtain new verification scores:

$$\bar{C}^n(s, u) = \langle w_n^n(s), \bar{w}^n(u) \rangle \quad (9)$$

On the other hand, the direct combination of i-vectors associated to different Λ^n systems is not possible. Therefore, instead of fusing the i-vectors provided by each system, we consider a combination at score level based on an arbitrary operator $f(\cdot)$, i.e. $\max(\cdot)$ or $\text{avg}(\cdot)$ [19]. For each model-sentence pair

(s, u) the final multi-channel score is then computed as a function of the single system scores:

$$\hat{C}(s, u) = f\left(\bar{C}^1(s, u), \dots, \bar{C}^N(s, u)\right) \quad (10)$$

Figure 2 shows a summary diagram of the method proposed in this section. Note that this score fusion can be applied on each channel m over the N systems:

$$\hat{C}_m(s, u) = f\left(C_m^1(s, u), \dots, C_m^N(s, u)\right). \quad (11)$$

3. Experiments and Results

In our experiments, i-vectors are based on Mel-Frequency Cepstral Coefficients (MFCCs) features extracted in 20ms frames, with 10ms overlap. Each feature vector is composed of 15 static MFCCs with its derivatives, totalling 30 dimensions. The total variability matrix is estimated according to [20], starting from a gender independent UBM composed by 1024 Gaussian mixtures. The UBM is trained through the expectation maximization (EM) algorithm. The dimension of the total variability subspace is fixed to 400. Zero and first-order sufficient statistics of the training sets are used for training the TV matrix \mathbf{T} : 10 EM iterations are applied for both ML and minimum divergence update. The covariance matrix is not updated in any of the EM iterations. The estimated \mathbf{T} matrix is in turn used for extraction of the total variability factors from the speech segments as described in [20]. Finally, the resulting factor vectors are normalized to be of unit length, which we will refer to as i-vectors. Whenever more than a speech utterance per speaker is available for enrolment, the target speaker i-vector is the result of averaging the i-vectors obtained from the several enrolment utterances. After some empirical analysis we adopted the average operator as score combination in Eq. 10.

3.1. Data contamination

A simulated data-set has been created based on the convolution of clean speech segments with a set of Room Impulse Response (RIR)s, measured in the target apartment [21]. Figure 3 shows the layout of the apartment, the microphone positions and the grid of possible source positions and orientations.

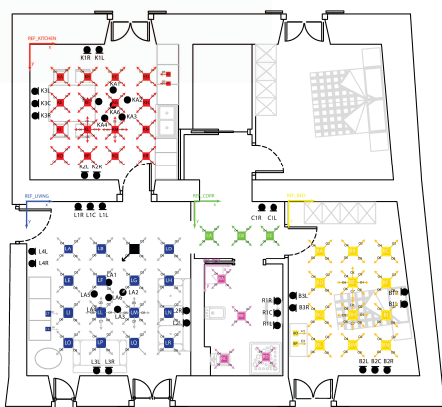


Figure 3: Layout of the apartment used in the experiments. Squares and arrows indicate the possible speaker positions and orientations. The black square and arrow represent the training and enrolment position.

Particularly, we established that the “fixed” position/orientation for speaker training/enrolment is in the

Livingroom. Conversely in the verification stage the speaker positions and orientations are randomly selected among those available in 3 rooms: Kitchen (red), Livingroom (blue) and Bedroom (yellow), choosing a different position/orientation pair for each test sentence. For each room, one microphone per wall/ceiling is selected among those available (i.e. 4 microphones in the Kitchen, 5 in the Livingroom and 3 in the Bedroom). For comparison purposes, we created an additional test-set in which the speakers are in the enrolment position. The latter test-set is referred to as *matched* test-set, in contrast to the realistic *mismatch* test-set with random speaker positions. In this work, we have considered the effects of reverberation only and no additive noise has been incorporated into the data simulation process.

The multi-channel reverberant data-set has been created from the Portuguese corpus *Base de Dados em Português eUropeu, vocabulário Largo, Independente do orador e fala Contínua* (BD-PUBLICO) [22]. It contains data from 60 female and 60 male speakers. Speakers were divided into two gender-balanced disjoint sets: target and non-target speakers. The non-target speakers’ data was used to train the UBM, TV matrices and centering and whitening transformation parameters. For the enrolment of the target speakers, we limited the total duration of speech to ~ 60 s per speaker. The test set consisted of data that was not used in the enrolment sets, totalling 3107 test utterances (1045, 1000 and 1062 in the Kitchen, Livingroom and Bedroom respectively for the *mismatch* case). The total number of gender-independent trials for SPKV is 186420.

3.2. Matched test-set results

Table 1 reports the performance in terms of Equal Error Rate (EER) in matched conditions on the BD-PUBLICO data-set for the proposed methods¹. In the matched test-set $N = M = 5$ and a perfect match between system Λ^n and channel $x^n(t)$ occurs.

		Match					
T	ch	LA6	L1C	L2R	L3R	L4R	Avg
	LA6	<i>1.95</i>	2.30	2.30	2.25	2.39	1.69
	L1C	2.29	<i>2.09</i>	2.64	2.38	2.40	1.88
	L2R	2.08	2.08	<i>1.83</i>	2.19	2.17	1.54
	L3R	2.19	2.32	2.23	<i>1.91</i>	2.39	1.66
	L4R	2.31	2.28	2.57	2.30	<i>1.85</i>	1.78
	Λ^*	1.63	1.49	1.47	1.46	1.43	1.26
	$f(\cdot)$	1.50	1.57	1.64	1.53	1.45	1.31

Table 1: EER(%) results for the proposed TV multi-channel distant verification approaches in matched conditions.

The 5×5 inner cells on the top left part of the table, identified with a channel dependent system row and a test channel column, correspond to the systems described in Eq. 7 (cell $n \times m$ is related to $C_m^n(s, u)$). The diagonal, in italics, refers to the N single-channel matched baselines. As one can expect, better results are generally achieved in presence of perfect match between the enrolment and the test propagation characteristics, these results can be considered a sort of upper-bound for single-channel distant speaker verification. Very similar performance across the systems and the channels can be observed: since the propagation characteristics are effectively captured by the channel-dependent system Λ^n , the selection of the system is not

¹EER and DET plots are obtained using the Bosaris toolkit [23].

Mismatch			
Scores	Single channel Λ^n	Combined Λ^*	Distributed $f(\cdot)$
raw	4.25	3.54	2.98
processed	2.57	1.50	1.45

Table 2: EER(%) results for the proposed TV multi-channel distant verification approaches in mismatch test-set. The performance in the single-channel baseline is the average of the performance of each single-channel system.

critical in the matched scenario. Counter-wise, a drop in performance can be generally observed when the off-diagonal performances are considered: in this case there is not a perfect match of propagation conditions. According to complementary experiments, the gap is more noticeable when no centering, whitening and score normalization is applied, meaning that some compensation is achieved thanks to these processing. The last column “Avg” of Table 1 corresponds, for each channel-dependent system Λ^n , to the approach described in Eq. 9 based on average test vectors: general improvements can be observed. The combined TV approach corresponds to the row identified with “ Λ^* ”: the last column in bold reports the results obtained with the multi-channel system in Eq. 6, while the other columns report the performance when considering a single channel during test. The row identified as “ $f(\cdot)$ ” refers to the system described by Eq. 11 for each of the test channel column m . Finally, the performance of the distributed multi-channel verification system, described in Eq. 10, is presented in the bottom right corner in bold.

Regarding the distributed approach we can observe consistent improvements when comparing to the corresponding single-channel solutions. Concerning the combined approach, it also brings a consistent improvement over the baseline in all cases. When multiple channels are applied in the test stage the overall combined approach reaches an EER of 1.26%, far lower than the single-channel baselines which range between 1.83% and 2.08%, and comparable to the 1.31% achieved with the distributed approach.

3.3. Mismatched test-set results

The experimental results in the mismatch case, where the speaker is free to move in 3 rooms of the apartment, are reported in Table 2. In this case single-channel baselines correspond to each combination of the N Λ^n systems with the M channels available in the room where the speaker is located. Since only a partition of the original verification trials occurs at each room, comparable results of the 5×12 combinations cannot be reported. Instead, in Table 2 we report the average EER of 5×12 systems (that process a portion of the trials) in contrast to the overall proposed systems (pooling the verification scores of the trials occurring at the 3 rooms). In fact, the average performance is significant since the behaviours of the 5×12 systems are rather uniform. The table also reports the results with and without vector and score post-processing (i.e. centering and whitening and score normalization). Interestingly, the single channel average EER in mismatch conditions is very similar to the off-diagonal figures shown in the matched case. Both the distributed and the combined approaches obtain remarkable performance improvements with respect to the corresponding baselines. By means of these channel combination methods we are able to obtain better performances on the mismatch scenario to those reported in the diagonal of the matched case. Moreover, the EER in this mismatch test-set is compar-

able to what obtained with the proposed multi-channel solutions in the matched scenario: 1.50% vs 1.25% and 1.45% vs 1.31% with the distributed and combined approaches, respectively. As a result we can claim that the proposed methods offer a position independent SPKV solution.

It is worth noting that without post-processing the distributed solution behaves better than the combined approach. Post-processing gives a substantial benefit to both methods resulting in nearly equivalent performance. This is clear in Figure 4 that shows the DET curves for the two proposed approaches with and without post-processing. Probably, the boost provided by the post-processing pushes considerably the performance towards the lower bound, masking in practice any difference in the behaviours of the two approaches.

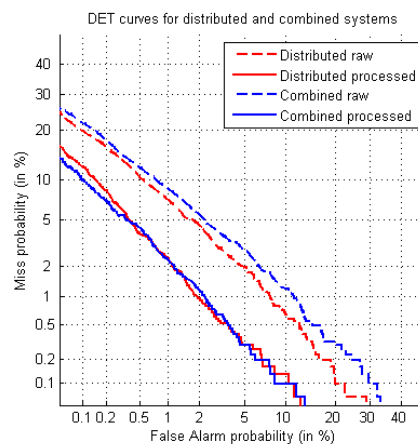


Figure 4: DET curve in the mismatch test-set for the two proposed multi-channel solutions with and without vector and score post-processing.

4. Conclusions

In this work we presented a study on multi-channel speaker verification in reverberant environments, addressing in particular the mismatch between the speaker position in the enrolment and test stages. We devised two approaches, based on the state of the art TV modeling technique, which take advantage of the complementary information captured by multi-channel recordings: in one case multiple channel-dependent TV matrices are adopted, while in the other a single channel-independent matrix is used. The proposed solutions are able to improve the baseline performance of single channel systems, achieving up to an EER of 1.26% and 1.45% in matched and mismatched conditions, respectively. Overall, the investigated solutions proved to be robust against mismatch between the enrolment and test positions of the speakers, even improving the performance of the single-channel baselines in matched conditions. A further advantage is that the proposed methods not only do not need a perfect matching between the training, enrolment and test propagation conditions, but also the selection of a specific processing channel is avoided, which reduces the possibility for a performance degradation due to inappropriate microphone selection.

Future work will address the adoption of more advanced methods to combine vectors obtained from different channels (i.e. PLDA [24]) and more effective combinations of the scores of the distributed systems. The solutions for channel mismatch robustness proposed by [11, 12] will also be investigated for comparison or to further improve the performance of our multi-channel solutions.

5. References

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