LAUGH BETRAYS YOU? LEARNING ROBUST SPEAKER REPRESENTATION FROM SPEECH CONTAINING NON-VERBAL FRAGMENTS

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ABSTRACT

The success of automatic speaker verification shows that discriminative speaker representations can be extracted from neutral speech. However, as a kind of non-verbal voice, laughter should also carry speaker information intuitively. Thus, this paper focuses on exploring speaker verification about utterances containing non-verbal laughter segments. We collect a set of clips with laughter components by conducting a laughter detection script on VoxCeleb and part of the CN-Celeb dataset. To further filter untrusted clips, probability scores are calculated by our binary laughter detection classifier, which is pre-trained by pure laughter and neutral speech. After that, based on the clips whose scores are over the threshold, we construct trials under two different evaluation scenarios: Laughter-Laughter (LL) and Speech-Laughter (SL). Then a novel method called Laughter-Splicing based Network (LSN) is proposed, which can significantly boost performance in both scenarios and maintain the performance on the neutral speech, such as the VoxCeleb1 test set. Specifically, our system achieves relative 20% and 22% improvement on Laughter-Laughter and Speech-Laughter trials, respectively. The meta-data and sample clips have been released at Repo.

Index Terms— Speaker Verification, Non-Verbal, Laughter.

1. INTRODUCTION

The application of deep learning techniques makes Automatic Speaker Verification (ASV) achieve a spurt of progress. In recent years, impressive performance has been achieved by constructing deep speaker embedding with large-scale neural networks like ECAPA-TDNN[1] and ResNet[2]. Margin-based loss functions like AM-SoftMax[3] as well as AAM-SoftMax[4] further enforce higher similarity for intra-class samples and larger distance for inter-class samples. Speaker verification models and strategies strongly depend on large-scale dataset with massive speech utterances from lots of speakers. However, not only verbal speech contains speaker information, non-verbal components still carry the speaker information intuitively. Several studies have investigated and analyzed the effect of various non-verbal sounds, such as breath, whistle, etc., on the task of speaker recognition[5, 6, 7, 8]. Laughter is the most frequent non-speech fragment in our daily conversations. Therefore, this paper focuses on learning speaker representation of laughter and exploring the extraction of speaker embeddings from the non-verbal speech segments.

Early studies find that the acoustic feature of laughter shares many similarities (like RMS amplitude) and differences (like the time between syllables) [9, 10] with speech features. Researchers have found that laughter exhibits higher formant frequencies than neutral speech [11], which can be utilized as a speaker-specific identifier. Recently, the deep laughter feature has become popular in speech processing. But studies on laughter based speaker verification still are relatively scarce. Dumpala et.al[12] incorporates i-vector to conduct recognition tasks on speech-laughter utterances and laughter utterances. Zhang et.al[13] employs d-vector to capture embeddings from short-duration trivial events, including laughter. However, those studies do not have a unified benchmark. Compared to previous works, our experiments are conducted on current popular datasets. We adopt a laughter detection tool to retrieve the laughter data from VoxCeleb and CN-Celeb datasets and construct a laughter speaker verification benchmark. We also propose a Laughter-Splicing based Network (LSN) approach to improve the speaker representation ability of laughter sound. Our contribution can be summarized as follows:

- utilizing laughter detection model to extract laughter clips from the wild data, such as VoxCeleb and CN-Celeb.
- designing two evaluation scenarios and the corresponding trials as benchmarks.
- proposing a novel method named Laughter-Splicing based Network (LSN) to enhance the quality of speaker embeddings in the non-verbal scenario.

The remaining paper is organized as follows. Sec.2 describes the pipeline of our laughter-clips extraction and the designing detail of evaluation trials. Sec.3 introduces our proposed LSN model. Sec.4 shows the experimental setup and results. Conclusions are drawn in Sec.5.

2. BENCHMARK DESIGN

In this part, we will introduce the pipeline of laughter extraction from the wild data and the details of trial construction in the evaluation set.

2.1. Dataset Usage

- VoxCeleb 1&2 [14, 15] are the most popular datasets in speaker verification field, which include 1,237,578 utterances...
Laughter candidates are short clips of utterances from 859 speakers. All of these speakers’ utterances constitute $U_{\text{candidates}}$ and utterances from the rest of speakers compose $U_{\text{neutral}}$. We can easily derive that $U_{\text{total}} = U_{\text{candidates}} \cup U_{\text{neutral}}$. $U_{\text{laughter}}$ are constructed by clean laughter clips we filtered from laughter candidates, and $U_{\text{qualified}}$ contains their original utterances from which they are segmented. By conducting laughter detection on $U_{\text{total}}$ and binary detecting classification on laughter candidates, clean laughter clips can be finally derived to construct evaluation trials.

2.2. Pipeline

The laughter extraction pipeline is shown in Fig. 1. Specifically, we adopt the following steps:

• Step.1 Applying the laughter-detecting toolkit to distinguish candidate laughter clips.

• Step.2 Training a binary laughter detection classifier based on labeled pure laughter as well as neutral speech data selected from Vox-Celeb and CN-Celeb subset.

• Step.3 Inferring the laughter detection classification score for each clip in the laughter candidate utterances.

• Step.4 Selecting final laughter clips with high scores.

Laughter extraction. We used the toolkit proposed by Gillick et.al [18] to capture laughter clips at the first stage, this tool is relatively robust in noisy environments. Each utterance in Vox-Celeb and CN-Celeb (defined as $U_{\text{total}}$) is checked at the segment level to seek possible laughter clips with a relatively loose standard. Finally, 10,487 non-verbal laughter segments have been selected from 859 speakers as laughter candidates. Here $U_{\text{candidates}}$ is denoted as the set of all utterances from these utterances. Therefore, the remained utterances from 7541 speakers, which consist of neutral speech without any laughter segments, are described as $U_{\text{neutral}}$.

Binary classification. Since the aforementioned laughter detection tool[18] can not precisely truncate qualified laughter clips or segments, we additionally train a laughter-speech binary detection classifier to determine the candidate laughter segments. The NVV and MagicData-RAMC are denoted as pure laughter samples $U_{\text{pure}}$ and the $U_{\text{neutral}}$ are regarded as neutral speech samples. In this paper, the ResNet18 is adopted as the backbone of our segment-level laughter detection classifier. Since the laughter and speech data are not balanced, the Focal Loss (FL) [19] is adopted to mine hard misclassified samples, which are laughter segments in our experiment. The formula is displayed as follows:

$$FL(p_t) = -\alpha_t(1-p_t)\gamma \log(p_t)$$ (1)

$p_t$ is denoted as the predicted probability of the target class. The hard samples can be well-classified by controlling modulating factor $(1-p_t)\gamma$. After that, each laughter candidate segment achieves a probability value by the laughter detection classifier. Then, by setting up a threshold, the reliable laughter clips $U_{\text{laughter}}$ can be filtered, and the original utterances (clips are truncated from those utterances) of them are called $U_{\text{qualified}}$. By now, we could easily obtain that $U_{\text{qualified}} \subseteq U_{\text{candidates}} \subseteq U_{\text{total}}$. The detailed file names and time stamps can be found in our repository. After manually listening to audio in $U_{\text{laughter}}$, we discover that the $U_{\text{laughter}}$ contains speech clips with entire laughter as well as partially-occupied laughter.

2.3. Trial construction

We construct two types of trials: Speech-Laughter (SL) and Laughter-Laughter (LL). Each testing laughter utterance has an
Table 1. The brief information of data composition in $U_{laughter}$. Cn-Celeb-ent and Cn-Celeb-int represent CN-Celeb2 utterances with entertainment and interview scene labels, respectively.

|                        | Utt. Nums | Spk. Nums | Duration Avg (s) |
|------------------------|-----------|-----------|------------------|
| Vox-Celeb clips        | 1,206     | 691       | 1.387            |
| Cn-Celeb-int clips     | 275       | 96        | 1.472            |
| Cn-Celeb-ent clips     | 214       | 81        | 1.518            |
| Total                  | 1,695     | 858       | 1.417            |

Then we collect speaker-wise representation by calculating the similarity score in our training set, we seek a neighbor speaker average embedding of each speaker. Finally, for each speaker in training data are extracted as our Laughter-Neighbor Data Augmentation (LNDA) approach.

Empirically, Laughter has more commonalities when compared with neutral speech. The formula is shown in the following. $Sim(\cdot)$ indicates the cosine similarity. Ultimately, each speaker in our training data is corresponding to one speaker in $U_{pure}$. There are inevitably multiple training speakers corresponding to one pure laughter speaker, as the number of speakers in $U_{pure}$ is limited. This augmentation method is denoted as LNDA Many-to-One (LNDA-M2O). In addition, we also proposed an alternative method, e.g., each speaker in pure laughter set $U_{pure}$ is associated with only one speaker in training data. This method is denoted as LNDA One-to-One (LNDA-O2O).

After that, before we feed training audio from speaker $i$ into our model, a random laughter segment from speaker $S(i)$ in $U_{pure}$ is selected and concatenated at the beginning or end of the neutral speech to make up an augmented utterance. Then, the augmented utterance will flow into our backbone together with the original utterance.

3. Model Backbone

Fig 2 shows the framework of our network structure. Augmented and original utterances are put into weight-shared encoders in parallel to extract speaker embeddings. Sub-center ArcFace loss [20] function is employed as our classification loss function, which can help to distinguish speech with laughter from different speakers to a large extent with robustness. Simultaneously, contrastive loss [21] between speaker embeddings promotes the compactness of representations between speech containing laughter and neutral speech. The formula is shown in the following.

$$L_{contrastive} = -\frac{1}{N} \sum_{i=1}^{N} \log \frac{e^{sim(z_i, z_j)}/\tau}{\sum_{k=1,k\neq i}^{N} e^{sim(z_i, z_k)}/\tau} \quad (3)$$

$$L = \lambda \cdot L_{classifier} + L_{contrastive}. \quad (4)$$

In Eq.3, $\text{sim}(\cdot)$ denotes cosine similarity and $N$ indicates batch size. $z_i$ and $z_j$ are speaker embeddings of the original utterance and the LNDA utterance, respectively. With a weight coefficient $\lambda$, $L_{classifier}$ and $L_{contrastive}$ can be leveraged to optimize our model jointly as shown in Eq.4.
Table 3. The experimental performance of various speaker verification systems in terms of EER. The M1 and M2 models are our baseline systems and are optimized solely by $U_{\text{neutral}}$ and $U_{\text{pure}}$, respectively. ResNet34-Subcenter with LNDA and contrastive learning block compose our proposed LSN method.

| ID  | Model                                        | Speech-Speech | Laughter-Laughter | Speech-Laughter |
|-----|---------------------------------------------|---------------|-------------------|-----------------|
|     |                                             | Vox-O[\%] | Vox-E[\%] | Vox-H[\%] | LL-O[\%] | LL-H[\%] | SL-O[\%] | SL-H[\%] |
| M1  | ResNet34-ArcFace (with $U_{\text{neutral}}$) | 0.814        | 1.061       | 1.882       | 23.052   | 23.821   | 17.838   | 19.145   |
| M2  | ResNet34-ArcFace (with $U_{\text{pure}}$)  | 2.696        | 2.960       | 4.907       | 27.403   | 28.024   | 21.490   | 22.295   |
| M3  | ResNet34-ArcFace+LNDA-M2O                  | 1.228        | 1.434       | 2.514       | 19.266   | 21.042   | 17.826   | 19.203   |
| M4  | ++SubCenter                                | 1.165        | 1.335       | 2.417       | 18.896   | 20.433   | 17.684   | 18.849   |
| M5  | +++Contrastive(LSN)                        | 1.680        | 1.816       | 3.418       | 18.312   | 20.268   | 13.968   | 15.128   |
| M6  | ResNet34-ArcFace+LNDA-O2O                 | 3.121        | 3.841       | 6.605       | 22.245   | 23.593   | 17.257   | 18.363   |

4. EXPERIMENTAL RESULT

4.1. Implementation Details

Laughter Extracting. The minimum duration of each clip is set to one second to guarantee the quality of audio segments, and the detection scoring threshold is 0.3. The ResNet-18 based binary classification model, with $\{32, 64, 128, 256\}$ channel numbers and a statistic pooling layer has been trained for 12 epochs.

Network. The speaker embedding extractor mentioned in Sec 3.1 adopts ResNet-34 as backbone followed by a statistic pooling layer. The widths (channel number) of the residual blocks are $\{64, 128, 256, 512\}$. The output of a fully connected layer with 256 dimensions followed after the pooling layer is adopted as the speaker embedding layer. The Sub-Center ArcFace (k=3, m=0, s=32) classifier is introduced to identify speakers.

Training Details. In our pre-training stage, the detailed configuration is the same as in [22]. In our proposed LSN method, we utilize the intersection of $U_{\text{neutral}}$ and VoxCeleb2 as the training set, which includes 934,166 utterances from 5,425 speakers. While all the training data has been explored in LNDA-M2O, only a portion of it has been utilized in LNDA-O2O, which includes 28,138 utterances from 184 speakers. We adopt 80-dimensional log Mel-Filterbank energies with a frame length of 25ms and hop size of 10ms. 3 seconds segment is randomly truncated before flowing into the encoder, and 1 second laughter segment is spliced when passing through the LNDA module. The SGD optimizer is employed to update the model parameters. We adopt the multi-step learning rate (LR) scheduler with 0.1 initial LR and our optimization terminates after the LR drops to 1e-5. The weight coefficient $\lambda$ of Eq.4 is set 0.05 and the temperature $\tau$ of contrastive loss is 0.5.

Evaluation Measures. Cosine similarity is used for scoring. Enrollment and test utterances are trimmed to same duration (4 seconds in this experiment) to alleviate side-effect from the length gap between enrollment and test utterance. Verification performance is measured by Equal Error Rate (EER).

4.2. Experimental result and analysis

Baseline System. As is shown in Table 3, our baseline systems (first two models) shows a degraded performance in Laughter-Laughter (LL) and Speech-Laughter (SL) evaluation protocols. Although ResNet34-ArcFace optimized with $U_{\text{neutral}}$ presents an excellent performance on the VoxCeleb test set, it is not robust against laughter sounds. Meanwhile, training with very limited pure laughter easily results in overfitting on its training dataset, which does not perform well either.

Our Methods. To demonstrate the effectiveness of our method, we have conducted ablation experiments illustrated in Table 3. By incorporating LNDA-M2O, we achieve a dramatic improvement in the Laughter-Laughter evaluation set. Specifically, there is a relatively 16.4% improvement in LL-O and 11.67% in LL-H improvement in terms of EER. However, compared with LNDA-M2O, LNDA-O2O exhibits a weaker improvement on LL trials accompanied by a significant degradation on the Speech-Speech (Vox) evaluation protocol. We conjecture that the shortage of training data and the existence of mis-matched speaker pairs may mitigate the positive effect of our LNDA. On the other hand, LNDA makes little improvement on the Speech-Laughter test set. We think it might be because the LNDA enlarges the inter-class distance of laughter rather than reducing the intra-class embedding distance between laughter and speech.

When we substitute the standard ArcFace Loss with the Sub-Center ArcFace Loss, there is a minor improvement in LL and SL set. Since our proposed LSN has been leveraged, the performance on LL and SL evaluation set can be dramatically boosted. In detail, our proposed system gains relatively 20.57% and 14.9% enhancement of EER on LL-O and LL-H, respectively. Concurrently, the contrastive loss can condense the gap of speaker representation between intra-class laughter and speech samples. That also indicates that the proposed approach can achieve a great improvement on the SL evaluation set, with relatively 21.69% and 20.98% improvement on EER. Besides, with improvement on LL and SL sets, there is a little degradation on the VoxCeleb test set, but the degradation is tolerable.

5. CONCLUSION

This paper provides a laughter speaker verification benchmark based on the VoxCeleb and CN-Celeb. We propose a Laughter-Splicing based Network (LSN) to learn robust speaker representation from speech containing non-verbal segments. In practical terms, this paper adopts a laughter-detecting script to capture laughter clips in VoxCeleb and CN-Celeb. After the binary classification procedure, evaluation trials under two different scenarios are constructed based on those clips. Then the LNDA module as well as contrastive loss makes up our proposed LSN method, which helps to learn robust speaker representation from speech containing laughter segments. Finally, with the LSN method, our system achieves a relative 20% improvement on both the Laughter-Laughter and Speech-Laughter test sets.
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