This paper presents a description of STC Ltd. systems submitted to the NIST 2021 Speaker Recognition Evaluation for both fixed and open training conditions. These systems consist of a number of diverse subsystems based on using deep neural networks as feature extractors. During the NIST 2021 SRE challenge we focused on the training of the state-of-the-art deep speaker embeddings extractors like ResNets and ECAPA networks by using additive angular margin based loss functions. Additionally, inspired by the recent success of the wav2vec 2.0 features in automatic speech recognition we explored the effectiveness of this approach for the speaker verification filed. According to our observation the fine-tuning of the pretrained large wav2vec 2.0 model provides our best performing systems for open track condition. Our experiments with wav2vec 2.0 based extractors for the fixed condition showed that unsupervised autoregressive pretraining with Contrastive Predictive Coding loss opens the door to training powerful transformer-based extractors from raw speech signals.

For video modality we developed our best solution with RetinaFace face detector and deep ResNet face embeddings extractor trained on large face image datasets.

The final results for primary systems were obtained by different configurations of subsystems fusion on the score level followed by score calibration.

**Index Terms**— ResNet, speaker recognition, wav2vec.

1. INTRODUCTION

Today’s state-of-the-art [1, 2, 3, 4, 5] speaker recognition systems are based on very deep convolutional neural networks (ResNets, ECAPA, Extended TDNNs) which use log Mel Filter Bank features as input and are trained on large datasets using additive angular margin loss functions and different optimization strategies. The simple cosine or PLDA scoring are usually used as an extractors back-end. In our study we decided to follow this principles while developing systems for the SRE 21 Challenge.

In contrast to the past NIST SREs [6, 7, 8] the key challenges provided by new NIST SRE 21 datasets [5] are multi-channel and multi-language speaker recognition based on audio-from video and telephone speech segments. Taking this into account the top performing systems should be well calibrated and robust for the cross-channel and same-channel microphone and telephone conditions. To this end we considered both 8 kHz and 16 kHz acoustic features to train different system.

Inspired by the success of wav2vec 2.0 in speech recognition tasks [9, 10] in our work we performed new study of wav2vec 2.0 model fine tuning for speaker recognition tasks. The experiments with wav2vec models were conducted for both fixed and open track conditions.

It should be noted that wav2vec 2.0 models are powerful transformer based models which take raw speech signals as input and incorporate multi-head attention mechanism on the deep layers.

During our investigations we found out that last classification layers of the extractors contain useful information for speaker verification. We explored some naive ideas of using this information by doing speaker verification on the classification layer output (cl-embeddings) with simple cosine similarity metric scoring.

This paper presents the detailed description of the systems submitted by STC Ltd. to NIST SRE 2021 and its performance estimates obtained on the dev set.

2. SPEAKER VERIFICATION SYSTEMS

2.1. Train datasets

**Fixed-track train set.** This set consists of data from

- NIST SRE CTS Superset (LDC2021E08);
- 2016 NIST SRE Evaluation Set (LDC2019S20);
concatenated VoxCeleb 1 and 2 datasets.

For augmentation purposes we used standard Kaldi augmentation recipe (reverberation, babble, music and noise) with freely available MUSAN and simulated Room Impulse Response (RIR) datasets. Additionally, we applied SpecAugment [11] technique and simulated codecs effects by different types of low-pass, high-pass, band-pass and band-stop filters. As well we simulated telephone and microphone channels with different types of Finite Impulse Responses (FIR), computed on 2021 NIST SRE Development Set.

In total, this training set contains 725,983 records from 14,271 speakers.

Open-track train set. This set was used for open-track systems training. For building it we used a wide variety of different datasets containing telephone and microphone data from private datasets and from those available online:

- Switchboard2 Phases 1, 2 and 3;
- Switchboard Cellular;
- Mixer 6 Speech;
- NIST SREs 2004 - 2010;
- NIST SRE 2018 (eval set);
- concatenated VoxCeleb 1 and 2;
- RusTelecom v2;
- RusIVR corpus.

RusTelecom v2 is an extended versions of private Russian corpus of telephone speech, collected by call-centers in Russia. RusIVR is a private Russian corpus with telephone and media data, collected in various scenarios and recorded by different types of devices (telephone, headset, far-field microphone, etc). In order to increase the amount and diversity of the training data, we used Kaldi standard recipe in addition to augmentations described in section 2.1. In total, this training set contains 532,541 records from 33,466 speakers.

Open-track tuning set. This set is a subset of the 2.1 set and was used for tuning purposes only. Tuning set includes:

- Mixer 6 Speech;
- NIST SREs 2004–2010, 2016;
- concatenated VoxCeleb 1 and 2;
- RusIVR.

Additionally, we preprocessed NIST SREs datasets: we fixed a number of speaker markup errors, discarded files with multiple speakers in one utterance, and added microphone data for some speakers. We also filtered out hard examples from the training dataset using Sub Center ArcFace technique [12].

Standard Kaldi augmentation recipe was applied for this subset. In total, tuning set contains 336,724 records from 14,399 speakers.

2.2. Feature extraction

16kHz features. We use Log Mel-filter bank (MFB) energies with the following extraction settings:

- frame-length – 25 ms;
- frame-shift – 10 ms;
- low frequency – 20 Hz;
- high frequency – 7600 Hz;
- number of mel bins – 80.

After the features were extracted Mean Normalization (MN) over a 3-second sliding window was applied. In the fixed track we used Kaldi energy based VAD with energy threshold equal to 5.5. In open track U-net-based VAD was used instead.

8kHz features. We use Log Mel-filter bank (MFB) energies with the following extraction settings:

- frame-length – 25 ms;
- frame-shift – 10 ms;
- low frequency – 20 Hz;
- high frequency – 3700 Hz;
- number of mel bins – 64.

Similarly to 16kHz data Mean Normalization and VAD was applied further.

Raw audio signal processing. For our wav2vec based extractors we used raw 16 kHz audio. Kaldi-based energy vad was used for non-speech segment filtration. Additionally on-line augmentation scheme was used for raw audio samples with the following settings:

- MUSAN additive noise with $p = 0.25$;
- RIR convolution with $p = 0.25$;
- Frequency masking with $p = 0.25$;
- Time masking with $p = 0.25$;
- Clipping Distortion with $p = 0.25$.

Here $p$ is a probability of applying augmentation type for the sample in the training batch. All considered augmentations were applied in sequence.
2.3. Systems

This section contains the description of all single systems used for final submission in fixed and open tracks. All of them contain corresponding suffix for clarity.

During all stages of training and tuning processes AAM-Softmax loss was used with parameters $m$ and $s$ set to 0.35 and 32 respectively.

2.3.1. Fixed track

**ResNet34-16k-fixed.** This extractor is based on the ResNet34 model with some modifications, as well as set to one stride in the first BasicBlock and changed to a simple Conv2D stem block. This is a ResNet34 model trained on 16kHz version of 2.1.

**ExtResNet34-8k-fixed.** This is an extended Resnet34 model with bigger amount of filters on the frame level. It was trained on 8kHz version of 2.1. The model was initially trained for 15 epochs with 6 seconds speech segments using one cycle lr policy [13]. And then it was tuned for 3 epochs with crop size of 10 seconds and one epoch with 20 seconds.

**ExtResNet52-8k-fixed and ExtResNet52-16k-fixed.** These models are two similar extended ResNet52 architectures constructed from BasicBlocks. We trained these models on 8kHz and 16kHz versions of 2.1. We have used only clear data and half of the augmented data, chosen at random to speed up experiments. These models were trained with scheme described above except last step with tuning on 20 seconds segments.

**ResNet101-8k-fixed.** This model is a modified version of the standard ResNet101 architecture with Basic Blocks instead of BottleneckBlocks. It was trained on the 8kHz version of 2.1 for 20 epochs with a crop size of 5 seconds. The tuning procedure was performed twice for 3 epochs with 10 and 20 seconds segments length correspondingly.

**ResNet101-16k-fixed.** This model uses ResNet101 architecture with some modifications: set to one stride in the first BottleneckBlock and changed to a simple Conv2D stem block, which provides the basis for this extractor. Model was trained on the 16kHz version of 2.1 dataset with AMP in several stages with increasing crop size, loss margin and decreasing learning rate.

**ExtDResNet101-16k-fixed.** This model is based on ResNet101-8k-fixed architecture, which means that it also employs BasicBlocks. Additionally, it applies the model tweak from [14] called ResNet-D: adding a $2 \times 2$ average pooling layer in the downsampling block with a stride of 2 before the convolution, whose stride is changed to 1. The model was trained on 16kHz data from 2.1. The first 20 epochs speech segments of 5 seconds length are used and then the model is tuned for 10 and 20 seconds segments.

**ECAPA-TDNN-fixed.** Emphasized Channel Attention, Propagation and Aggregation in TDNN (ECAPA-TDNN), newly proposed in [15], is a modification of the standard Time Delay Neural Network (TDNN) architecture, containing Squeeze-Excitation (SE) blocks and Res2Net modules at the frame level and attentive statistic pooling (ASP) [16] instead of the usual statistic pooling. We use our implementation of ECAPA-TDNN architecture with the following parameters: the number of SE-Res2Net Blocks is set to 4 with dilation values 2,3,4,5 to blocks; the number of filters in the convolutional frame layers C is set to 2048; the number of filters in the bottleneck set to 1536 of the SE-Res2Net Block; ASP is used; embedding layer size is set to 1024; simple Conv1D with 2048 filters is used like a stem block. Model training is performed on 16kHz version of 2.1 dataset with AMP in several stages.

**ResNet101-16k-fixed & ECAPA-TDNN-fixed.** This system is the embedding level fusion of the ResNet101-16k-fixed and ECAPA-TDNN-fixed systems. However, instead of standard embeddings, the class posteriors logit embeddings were used here. In more details they are described in section 2.4.

**Wav2Vec-fixed.** For the fixed conditions we pretrained base wav2vec 2.0 [10] model using Contrastive Predicting Coding [17] scheme on SRE 21 train set with different augmentations types and cutting of non-speech segments. We used fairseq toolkit [18] \(1\) for its pretraining.

For training we used a part of fixed dataset - CTS Superset

\(1\)https://github.com/pytorch/fairseq/tree/main/examples/wav2vec
and Voxceleb 1, 2 with different sets of augmentations similar to described above in 2.1. We also applied Kaldi energy-based VAD for cutting long pauses in CTS_Superset. Model was pretrained for 7 epoch and then used as a starting point for our finetuning.

The main scheme of wav2vec 2.0 based speaker embeddings extractor is represented on Figure 1. As an effective wav2vec 2.0 back-end we applied two TDNN layers (the 1st with ReLU activation), statistic pooling layer to pool time series to single vector, maxout linear layer [19, 3] to get speaker embedding. We used AAM-Softmax based linear classification layer to fine-tune the extractor. In principle, one can pass output of the wav2vec directly to the statistics pooling layer. However, we find out that we can achieve better results if we pass them through the sequence of TDNN layers. The role of TDNN layers is to prefilter speaker specific information and to "prepare" wav2vec output time series for statistical pooling. According to our observations this approach let us achieve better results than direct statistical pooling of the wav2vec outputs. The TDNN blocks utilise context 1 of the input features and have 2048 dimension output. The obtained final speaker embedding size was 512. Additional note is that wav2vec part of the extractor could be freezed while tuning for downstream speaker recognition task. We observed that in this scenario the results can also be very good, but fine-tuning the whole extractors provides additional performance gains for speaker recognition system.

**SWIN-16k-fixed.** This model is based on a Shifted Windows Transformer architecture, proposed in [20] as an adaptation of standard transformers from NLP to computer vision task.

In our experiments we used the following architecture settings:

- image size: [80, 512]
- patch size: [2, 2]
- embedding dim of Swin Transformer Block 72
- model depths: [2, 4, 8, 4]
- number of attention heads for Swin Transformer Block: [3, 3, 3, 3]
- window size: 8.

We have added the statistics pooling layer and linear projection layer on top of the original model to obtain speaker embeddings. The model was trained on 16kHz version of 2.1 dataset with AMP in several stages with increasing crop size and loss margin and decreasing learning rate.

### 2.3.2. Open

For the final systems in open audio and audio-visual tracks we used systems from the fixed tracks described above as well as ones trained on the extended datasets.

**ECAPA-TDNN-open.** This model uses ECAPA-TDNN architecture [15] with the following parameters:

- 4 SE-Res2Net Blocks with dilation values 2,3,4,5
- 1024 filters in convolution frame layers C to match the number of filters in the bottleneck of the SE-Res2Net Block
- adaptive statistics pooling
- embedding size 512

We changed stem block to the stack of 4 Conv2D-BatchNorm2D-ReLU sequences with kernel size 3 and 32 filters for all convolution layers except the last one that used 1024 filters. Model was trained on 8kHz version of 2.1 dataset. The training process was performed in several stages with simultaneous increasing of the crop size (from 5 to 12 seconds) and loss margin and learning rate decreasing. After that the classification layer was reinitialised and the model was fine-tuned on 2.1 dataset.

**ResNet101-8k-open.** This model is based on ResNet101 with some modifications: maxout activation function for the embedding layer, stride of one in BootleneckBlock and simple Conv2D layer in place of stem block. Model was trained on 8kHz version of 2.1 dataset and tuned on Open-track tune set 2.1 similarly to ECAPA-TDNN-open.

**ResNet101-8k-open + ECAPA-TDNN-open** and **ResNet101-8k-open + ECAPA-TDNN-open filtered.** Both of these systems were prepared similarly to the systems for the fixed track: ResNet101-8k-open and ECAPA-TDNN-open were fused together on the cl-embeddings level (see section 2.4).

We eliminated less informative speaker classes in ResNet101-8k-open + ECAPA-TDNN-open filtered after the fusion to reduce the size of cl-embeddings. This technique produces better results on the dev set (Table 3).

**Wav2vec-(I,II,III,IV)-open.** These models were based on wav2vec 2.0 large architecture. For the open track we used large multi-lingual wav2vec 2.0 model XLSR 53 provided by facebook [18] on fairseq cite as a starting point for the fine-tuning. We used the same wav2vec Back-End as in our fix condition model. But the Wav2vec-(I,II,III)-open were trained using (8 sec, 12 sec, 14 sec) speech chunks durations respectively with different training strategies on 2.1 dataset. Wav2vec-IV-open was fine-tuned on 2.1 dataset using 14 sec speech chunks duration.

#### 2.4. Class posteriors logit embeddings

During our investigation we observed that the extractors classification layer outputs (namely class posteriors logit embeddings, or cl-embeddings) can be more informative than conventional pre-last layer embeddings. We realised that last classification layers obtained in closed classification task discriminative training contain useful information for the open...
task speaker discrimination. We explored some naive ideas of using this information by doing speaker verification on the classification layer output with simple cosine similarity metric scoring. For instance, the results of our experiments with cl-embeddings for two type of extractors ResNet101-16k-fix and ECAPA-TDNN-fix are presented in Table 1. Here cl-embeddings outperform conventional embeddings in terms of both the EER and minDCF. Moreover one can notice that cl-embeddings subspace allows to use effective and simple embeddings fusion procedure like weighted cl-embeddings sum. But this is possible if the extractors had the same training speakers classes or on intersected classes. From the results of Table 1 you can see such type of fusion is superior then simple score level fusion of the systems.

We use cl-embedding based fusion for ResNet101-16k-fix & ECAPA-TDNN-fix models and consider it further as single systems in section 4.

2.5. Scoring

We used Cosine similarity to distinguish speaker embeddings:

\[ S(x_1, x_2) = \frac{x_1^T x_2}{\|x_1\| \|x_2\|} \]  

(1)

where \((x_1, x_2)\) are speaker embedding vectors.

2.6. Score normalization

For all systems except of those based on wav2vec, adaptive scoring normalization technique (adaptive s-norm) from [21] is used. Here the normalized score for a pair \((x_1, x_2)\) can be estimated as follows:

\[ \hat{S}(x_1, x_2) = \frac{S(x_1, x_2) - \mu_1}{\sigma_1} + \frac{S(x_1, x_2) - \mu_2}{\sigma_2}, \]  

(2)

where the mean \(\mu_1\) and standard deviation \(\sigma_1\) are calculated by matching \(x_1\) against impostor cohort and similarly for \(\mu_2\) and \(\sigma_2\). A set of the \(n\) best scoring impostors are selected for each embedding pair when means and standard deviations are calculated. Additionally, we analysed the scores distribution for our single systems for dev set with and without source type match. The obtained results in Figure 2 confirm significant gap between the corresponding distributions. This led us to the idea of channel compensation.

For all systems scores we apply channel normalization technique, where the normalized score for a pair \((x_1, x_2)\) can be estimated as follows:

\[ \hat{S}(x_1, x_2) = \frac{S(x_1, x_2) - \mu_{ch}}{\sigma_{ch}}, \]  

(3)

where mean \(\mu_{ch}\) and standard deviation \(\sigma_{ch}\) are calculated for each pair of source type matching (tel-tel, mic-mic, tel-mic and mic-tel), obtained from source files headers and applied according to the the source type of \((x_1, x_2)\).

![Fig. 2: Comparison of target and impostor distributions with and without source type match obtained for Wav2Vec-fixed system: (a) no normalization applied, (b) channel normalization applied](image)

For those systems that used both normalization approaches, adaptive s-norm is applied before channel normalization.

Tables 2 and 3 demonstrate quality estimates in terms of EER, minDCF and ActDCF obtained on the dev set for each single system in its better configuration for fix and open tracks correspondingly.

3. FACE VERIFICATION SYSTEMS

We used a standard pipeline to solve the face verification problem: face detection, preprocessing of facial crops, embedding extraction, and scoring.

Firstly, a digital image of enroll or many frames of test video were processed using a face detector. The outputs of the face detector are the coordinates of the bounding box and the coordinates of the five facial landmarks. Secondly, we used
Table 1: Results of cl-embeddings, scores normalization and fusion for ResNet101-16k-fix and ECAPA-TDNN-fix systems for the audio track. Here cl-emb is the flag of using class posterior logits embeddings, ch-norm is channel scores normalization flag, s-norm – adaptive scores normalization flag respectively. The metrics were computed by NIST SRE 21 scoring tool.

| System name | cl-emb | s-norm | ch-norm | EER, % | minDCF21 |
|-------------|--------|--------|---------|--------|-----------|
| ResNet101-16k-fixed | -      | -      | -       | 8.04   | 0.408     |
|             | -      | ✓      | ✓       | 4.65   | 0.316     |
|             | -      | -      | ✓       | 5.28   | 0.36      |
|             | -      | ✓      | -       | 6.88   | 0.412     |
|             | ✓      | -      | -       | 6.93   | 0.35      |
|             | ✓      | ✓      | ✓       | **4.40** | **0.280** |
|             | ✓      | -      | ✓       | 5.06   | 0.309     |
|             | ✓      | ✓      | -       | 5.94   | 0.336     |
| ECAPA-TDNN-fixed | -      | -      | -       | 10.47  | 0.499     |
|             | -      | ✓      | ✓       | 7.09   | 0.451     |
|             | -      | -      | ✓       | 8.05   | 0.455     |
|             | -      | ✓      | -       | 10.34  | 0.593     |
|             | ✓      | -      | -       | 8.26   | 0.411     |
|             | ✓      | ✓      | ✓       | **5.94** | **0.352** |
|             | ✓      | -      | ✓       | 6.50   | 0.376     |
|             | ✓      | ✓      | -       | 8.07   | 0.486     |
| ResNet101-16k-fixed + ECAPA-TDNN-fixed (scores fusion) | ✓      | ✓      | ✓       | 3.97   | 0.253     |
| ResNet101-16k-fixed + ECAPA-TDNN-fixed (embeddings fusion) | ✓      | ✓      | ✓       | **3.50** | **0.230** |

Table 2: Fixed audio track single systems

| System                   | EER  | minDCF | actDCF |
|--------------------------|------|--------|--------|
| ResNet34-16k-fixed       | 6.1  | 0.377  | 0.39   |
| ResNet101-16k-fixed      | 3.5  | 0.23   | 0.233  |
| + ECAPA-TDNN-fixed       |      |        |        |
| Wav2Vec-fixed            | 7.57 | 0.426  | 0.45   |
| ResNet101-8k-fixed       | 4.24 | 0.322  | 0.333  |
| ExtDResNet101-16k-fixed  | 4.68 | 0.255  | 0.271  |
| SWIN-16k-fixed           | 6.72 | 0.443  | 0.465  |
| ExtResNet34-8k-fixed     | 3.96 | 0.301  | 0.305  |
| ExtResNet52-8k-fixed     | 3.67 | 0.266  | 0.278  |
| ExtResNet52-16k-fixed    | 3.65 | 0.28   | 0.282  |

Table 3: Open audio track single systems

| System                   | EER   | minDCF | actDCF |
|--------------------------|-------|--------|--------|
| ResNet34-16k-fixed       | 6.56  | 0.377  | 0.387  |
| ExtResNet34-8k-fixed     | 4.28  | 0.312  | 0.318  |
| ExtResNet52-8k-fixed     | 3.95  | 0.283  | 0.287  |
| ExtResNet52-16k-fixed    | 4.09  | 0.287  | 0.292  |
| ResNet101-8k-fixed       | 4.16  | 0.298  | 0.303  |
| ExtDResNet101-16k-fixed  | 4.7   | 0.265  | 0.277  |
| ResNet101-16k-fixed + ECAPA-TDNN-fixed | 6.69 | 0.426  | 0.435  |
| ResNet101-8k-open + ECAPA-TDNN-open | 2.88 | 0.209  | 0.215  |
| ResNet101-8k-open + ECAPA-TDNN-open-filtered | 2.94 | 0.2  | 0.207  |
| Wav2vec-I-open           | 4.49  | 0.27   | 0.276  |
| Wav2vec-II-open          | 2.88  | 0.246  | 0.258  |
| Wav2vec-III-open         | 3.68  | 0.2    | 0.203  |
| Wav2vec-IV-open          | 3.4   | 0.233  | 0.247  |
| SWIN-16k-fixed           | 6.91  | 0.446  | 0.459  |
| r101-l2_ecapa-l2_class_fusion | 3.32 | 0.257  | 0.271  |
the coordinates of the bounding box to create facial crops. The facial crops were aligned using the five facial landmarks, and then resized to \(112 \times 112\) pixels, and normalized. Thirdly, we extracted facial embeddings for enroll and test crops and, fourthly, we performed a scoring between enroll and test embeddings for each trial in development, and evaluation protocols.

3.1. Train datasets

We used the existing public face detector model based on RetinaFace [22] and focused on the high quality facial embedding extractor training. For this purpose we used the following databases: MS-Celeb-1M [23], VGGFace2 [24], TrillionPairs-Asians [25], DFW2018 [26] and our proprietary database.

3.2. Systems

3.2.1. Preprocessing stage

As described above, we used RetinaFace as a face detector. Since enrolls are described by an image, we used the face detector once to detect enroll crop of face. Tests are described by an video. We used FFmpeg [27] to extract every ten frames of test video and processed each test frame using RetinaFace. We did not use any face tracking algorithms.

As noted in the original paper [22], RetinaFace is a single-stage pixel-wise face localisation method, which employs extra-supervised and self-supervised multi-task learning in parallel with the existing box classification and regression branches. Each positive anchor outputs a face score, a face box, five facial landmarks, and dense 3D face vertices projected on the image plane. We used the coordinates of the bounding box to create facial crops and we used five facial landmarks, located in the area of the eyes, the tip of the nose, and the tips of the lips, to align facial crops. All facial crops have been resized to \(112 \times 112\) pixels. We illustrated the final facial crops after preprocessing of test frames from NIST SRE 2021 development set on Figure 3.

An important point to note in relation to visual data from NIST SRE 2021 development and evaluation set is header information in test video. The header of each test video contains rotation parameter. The rotation parameter determines the orientation of the frames from the test video. We read the rotation parameter to correctly orient test frames before performing the face detection procedure. We believe this parameter is important for the correct work of the preprocessing stage.

3.2.2. Facial embedding extractors

We trained two facial embedding extractors for the NIST SRE 2021 challenge. First embedding extractor was based on ResNet101-IR-SE-AN neural network architecture, where

IR means inverted residual [28], SE means squeeze-and-excitation [29], and AN means attentive normalization [30]. The embedding extractor was trained using MS-Celeb-1M, VGGFace2, TrillionPairs-Asians, DFW2018 datasets.

Second embedding extractor was based on ResNet100-PM neural network architecture, where PM means prototype memory [31]. Prototype memory is a face representation learning model, which alleviates "prototype obsolescence" problem (classifier weights (prototypes) of the rarely sampled classes, receive too scarce gradients and become outdated and detached from the current encoder state, resulting in an incorrect training signals) and allows training on a dataset of any size. We trained the ResNet100-PM embedding extractor using our proprietary database.

3.2.3. Scoring methods

ResNet101-IR-SE-AN’s embeddings and ResNet100-PM’s embeddings are normalized by length and can be distinguished by cosine similarity. Each trial in development and evaluation protocols contains a enroll and several test embeddings for visual modality. We used different scoring methods to compare enroll and test facial embeddings:

- calculating of maximum score (MS) between enroll embedding and test embeddings for each trial;
- calculating of score between enroll embedding and average test embedding (ATE) for each trial;
- calculating of score between enroll embedding and weighted average test embedding (WATE) for each trial (we don’t use test embeddings with small recognizability score to compute weighted average test embedding);
### Table 4: Visual track single systems

| System                          | EER   | minDCF | actDCF |
|--------------------------------|-------|--------|--------|
| ResNet101-IR-SE-AN + MRS       | 0.17  | 0.011  | 0.013  |
| ResNet101-IR-SE-AN + ATE       | 0.99  | 0.018  | -      |
| ResNet101-IR-SE-AN + W ATE     | 0.22  | 0.010  | 0.013  |
| ResNet101-IR-SE-AN + MRS       | 1.83  | 0.046  | -      |
| ResNet100-PM + MRS             | 1.32  | 0.013  | 0.018  |
| ResNet100-PM + ATE             | 1.82  | 0.018  | -      |
| ResNet100-PM + W ATE           | 1.66  | 0.017  | -      |
| ResNet100-PM + MRS             | 2.94  | 0.046  | -      |

### Table 5: Audio-visual track single systems (only visual)

| System                          | EER   | minDCF | actDCF |
|--------------------------------|-------|--------|--------|
| ResNet101-IR-SE-AN + MRS       | 0.10  | 0.009  | -      |
| ResNet101-IR-SE-AN + ATE       | 0.60  | 0.011  | -      |
| ResNet101-IR-SE-AN + W ATE     | 0.23  | 0.006  | -      |
| ResNet101-IR-SE-AN + MRS       | 2.40  | 0.055  | -      |
| ResNet100-PM + MRS             | 0.80  | 0.008  | -      |
| ResNet100-PM + ATE             | 1.10  | 0.011  | -      |
| ResNet100-PM + W ATE           | 1.00  | 0.010  | -      |
| ResNet100-PM + MRS             | 2.90  | 0.054  | -      |

- calculating of score between enroll embedding and test embedding with maximum recognizability score (MRS) for each trial.

Face detector can detect faces that cannot be recognized, no matter how capable the recognition system is. Recognizability, a latent variable, can therefore be factored into the design and implementation of face recognition systems. We implemented a measure of recognizability of a face image using idea from [32]. We compute a cosine distance to each test embeddings from an embedding of “unrecognizable identity” as a measure of recognizability. Final score of recognizability to each test embeddings was computed using the following mathematical expression:

\[ R_S(x_t, x_{ui}) = \left( \frac{1 - \frac{x_t^T x_{ui}}{\|x_t\| \|x_{ui}\|} - 0.35}{0.89} \right), \]

where \( x_t \) is a test embedding and \( x_{ui} \) is an embedding of “unrecognizable identity”. The values 0.35 and 0.89 in the expression above was chosen empirically to create a dynamic range for \( R_S \) between 0 and 1. We computed embeddings of “unrecognizable identity” to each our embedding extractors using unrecognizable images from WIDER FACE dataset [33].

### 4. FINAL SUBMITTED SYSTEMS

We tried Bosaris Toolkit [34] and greedy fusion algorithm [35] as a way to combine several single systems into one final submission system. Bosaris toolkit was also used for calibration. All calibration and fusion was trained on the SRE 21 dev sets. Table 6 reveals the results of all submitted systems on the dev set.

Greedy fusion is based on iterative process where the most promising system in terms of actDCF is selected to be added on each step until the mean value of actDCF on the dev set stopped improving.

Fused systems produced by Bosaris Toolkit, on the other hand, were difficult to interpret and often included quite similar systems in favor of more diverse ones. Moreover, having such a big list of systems to fuse we see that almost half of them obtain negative weights in the final fusion system.

Given all this, we decided to use following procedure for the final system preparation:

1. Calibration model training using BOSARIS Toolkit.
2. One modality fusion training (audio and video separately) using greedy algorithm.
3. Fusion of audio and video systems from step 2 for audio-visual track using BOSARIS Toolkit.
4. Final system score calibration by BOSARIS Toolkit.

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Table 6: Results of the systems prepared for the NIST SRE 21 challenge on the development set

| Fixed audio track | EER  | minDCF | actDCF | Open audio track | EER  | minDCF | actDCF |
|-------------------|------|--------|--------|-----------------|------|--------|--------|
| Primary           |      |        |        |                 |      |        |        |
| ResNet101-16k-fixed + ECAPA-TDNN-fix Wav2Vec-fixed ResNet101-8k-fixed ExtDResNet101-16k-fixed ExtResNet52-16k-fixed | 3.09 | 0.216  | 0.220 | Wav2vec-III-open ResNet101-8k-open + ECAPA-TDNN-open filtered SWIN16k-fixed ResNet101-16k-fixed + ECAPA-TDNN-fixed Wav2vec-IV-open Wav2vec-I-open ExtResNet52-16k-fixed ResNet34-16k-fixed ExtDResNet101-16k-fixed ExtResNet34-8k-fixed ExtResNet52-8k-fixed | 1.97 | 0.151  | 0.153  |
| Contrastive       |      |        |        |                 |      |        |        |
| ResNet101-16k-fix + ECAPA-TDNN-fix | 3.49 | 0.230  | 0.233 | Wav2vec-III-open ResNet101-8k-open + ECAPA-TDNN-open filtered | 2.38 | 0.156  | 0.161  |
| Single            |      |        |        |                 |      |        |        |
| ExtResNet52-8k-fixed | 3.67 | 0.266  | 0.278 | Wav2vec-III-open | 2.24 | 0.207  | 0.212  |
| Fixed visual track | EER  | minDCF | actDCF | Open visual track | EER  | minDCF | actDCF |
| ResNet101-IR-SE-AN + MS | 0.17 | 0.011  | 0.013 | ResNet101-IR-SE-AN + MS | 0.17 | 0.011  | 0.013  |
| ResNet101-IR-SE-AN + WATE | 0.17 | 0.010  | 0.012 | ResNet100-PM + MS | 1.32 | 0.013  | 0.018  |
| Fixed audio-visual track | EER  | minDCF | actDCF | Open audio-visual track | EER  | minDCF | actDCF |
| audio: ResNet101-16k-fixed + ECAPA-TDNN-fixed Wav2Vec-fixed ResNet101-8k-fixed ExtDResNet101-16k-fixed ExtResNet52-16k-fixed video: ResNet101-IR-SE-AN + MS | 0.10 | 0.002  | 0.003 | audio: Wav2vec-III-open ResNet101-8k-open + ECAPA-TDNN-open filtered SWIN16k-fixed ResNet101-16k-fixed + ECAPA-TDNN-fixed Wav2vec-IV-open Wav2vec-I-open ExtResNet52-16k-fixed ResNet34-16k-fixed ExtDResNet101-16k-fixed ExtResNet34-8k-fixed ExtResNet52-8k-fixed video: ResNet101-IR-SE-AN + MS | 0.10 | 0.001  | 0.002  |
| Contrastive       |      |        |        |                 |      |        |        |
| audio: ResNet101-16k-fix + ECAPA-TDNN-fix + WATE | 0.10 | 0.002  | 0.003 | audio: Wav2vec-III-open ResNet101-8k-open + ECAPA-TDNN-open filtered video: ResNet101-IR-SE-AN + MS | 0.10 | 0.002  | 0.003  |
| Single            |      |        |        |                 |      |        |        |
| ExtDResNet101-16k-fixed video: ResNet101-IR-SE-AN + MS | 0.13 | 0.003  | 0.003 | audio: Wav2vec-III-open video: ResNet101-IR-SE-AN + MS | 0.10 | 0.003  | 0.004  |
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