



Multi-Task Network for Noise-Robust Keyword Spotting and Speaker Verification using CTC-based Soft VAD and Global Query Attention

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Abstract

Keyword spotting (KWS) and speaker verification (SV) have been studied independently although it is known that acoustic and speaker domains are complementary. In this paper, we propose a multi-task network that performs KWS and SV simultaneously to fully utilize the interrelated domain information. The multi-task network tightly combines sub-networks aiming at performance improvement in challenging conditions such as noisy environments, open-vocabulary KWS, and short-duration SV, by introducing novel techniques of connectionist temporal classification (CTC)-based soft voice activity detection (VAD) and global query attention. Frame-level acoustic and speaker information is integrated with phonetically originated weights so that forms a word-level global representation. Then it is used for the aggregation of feature vectors to generate discriminative embeddings. Our proposed approach shows 4.06% and 26.71% relative improvements in equal error rate (EER) compared to the baselines for both tasks. We also present a visualization example and results of ablation experiments.

Index Terms: CTC-based soft VAD, global query attention, keyword spotting, speaker verification, multi-task network

1. Introduction

Progress in speech processing such as speech recognition and text-to-speech enables users to interact with smart devices through a voice user interface (VUI) rather than directly controlling it. But these techniques mainly focus on spontaneousness during the interaction. Before that, it is practically important that the interaction starts well. Among various criteria where the device recognizes the start of the interaction, two typical approaches are keyword spotting and speaker verification.

Keyword spotting (KWS) is the task of detecting the prescribed spoken term in the input utterance. Many studies and applications have focused on pre-defining the keyword(s) as their product name for wake-up or command words for specific actions [1, 2, 3]. Meanwhile, according to users' convenience and customizing needs, some research on open-vocabulary KWS has attracted interest since the users can define any keywords. A typical way to handle arbitrary keywords is to express any words as acoustic word embeddings which are fixed-dimensional vector representations of arbitrary-length words. These embeddings learn the acoustic similarity between pronunciations of words pair so that they can encode acoustic information. In training, some approaches use cross-entropy loss [4, 5], but triplet loss is mainly used because it can directly map the similarity to the relative distance in embedding space [6, 7, 8]. Recently, an approach that considers phonetic information based on connectionist temporal classification (CTC) [9] together showed good results [10]. Still, open-vocabulary KWS has a lot of room for improvement due to its challenging nature.

Speaker verification (SV) is the task of verifying the current speaker is a valid user. Here, we only deal with text-independent SV that does not have any restrictions on speech contents. SV requires an enrollment which is a process of registering the user's speaker identity. Then, speaker information is extracted from each input utterance and compared with the enrolled data. For successful SV, this speaker information must be expressed as a speaker discriminative representation. Recent the most powerful approaches based on deep neural networks are encoding speaker information as a fixed-dimensional vector representation, so-called speaker embedding. For learning discriminative embeddings, the networks are trained to classify speakers using cross-entropy loss [11, 12] or to group speakers in embedding space using triplet loss [13, 14]. The criticized problem of these systems is that a long utterance must be used for the input as well as the enrollment to extract speaker information reliably. It is because the amount of accumulated information increases as the speech lengthens under the assumption that there is one speaker for one utterance. To cover the problem, several approaches with pooling methods [15, 16, 17] have been proposed to weight the relevant speech frames. However, if the input length is not long enough, their performances are still degraded. Accordingly, many short-duration SV studies are being conducted to have high performance even with a short utterance [18, 19, 20, 21].

Even though acoustic and speaker information considers each other as a marginal feature that should be suppressed for robust discriminative learning, both KWS and SV have been handled independently. The ideal situation we think of is that the device can detect the keyword and verify the user at the same time using a short word-level utterance defined by the user. In other words, open-vocabulary KWS and short-duration SV will eventually operate with the same input in the same conditions.

So in this paper, we propose a multi-task network that performs both KWS and SV simultaneously by fully utilizing acoustic, speaker, and phonetic information. The multi-task network consists of an enhancement network, acoustic feature extraction network, speaker feature extraction network, and pooling network. The sub-networks are trained by being shared or contributed to each other. In this process, we also introduce novel techniques of CTC-based soft voice activity detection (VAD) and global query attention. We evaluate our proposed approach on discrimination tasks for KWS and SV, respectively. Experimental results demonstrate that acoustic, speaker, and phonetic domains are interrelated and it is effective to integrate them for learning discriminative embeddings even in noisy environments, open-vocabulary, and short-duration conditions. Also, we present a visualization example to intuitively understand the proposed methods, and results of ablation experiments to show the effectiveness of the multi-task network.

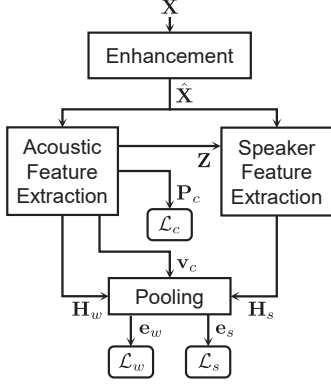


Figure 1: Overall architecture of the multi-task network.

2. Multi-Task Network

In this section, we introduce a multi-task network, which is composed of 4 sub-networks as depicted in Fig. 1. The more detailed structures of sub-networks are shown in Fig. 2.

2.1. Enhancement Network

With the basic belief that both KWS and SV performance can be improved when the noise component is removed from the input speech, we share the enhancement network with the next two sub-networks. The enhancement network comprises two dilated convolutional neural network (CNN) cascaded with two residual paths and subtractions (Fig. 2. (a)). Each dilated CNN consists of 5 convolution layers and their parameters are noted in Tab. 1. We extract a 256-dimensional log-magnitude spectrogram \mathbf{X} with a frame length of 25 ms and a shift of 10 ms yielding a $T \times 256$ input, where T is the number of frames. The dilated CNN estimates a spectral distortion which is then subtracted from the input. After two consecutive subtractions, we use the output feature vectors $\hat{\mathbf{X}}$ as an enhanced spectrogram.

2.2. Acoustic Feature Extraction Network

In the acoustic feature extraction network, we use two 2-layer bi-directional long short-term memory (LSTM) [22] modules hierarchically (LSTM_w^1 and LSTM_w^2 in Fig. 2. (b)) to represent $\hat{\mathbf{X}}$ as frame-level acoustic feature vectors, $\mathbf{H}_c \in \mathbb{R}^{T \times 512}$ and $\mathbf{H}_w \in \mathbb{R}^{T \times 512}$. Also, we input \mathbf{H}_c into linear layers, Linear_c^1 with ReLU activation and Linear_c^2 with log-softmax, to capture frame-level phonetic information:

$$\mathbf{Z} = \text{Linear}_c^1(\mathbf{H}_c) \in \mathbb{R}^{T \times 256}, \quad (1)$$

$$\mathbf{P}_c = \text{Linear}_c^2(\mathbf{Z}) \in \mathbb{R}^{T \times |\mathcal{C}|}. \quad (2)$$

\mathbf{P}_c is log-probabilities of observing CTC label sequence $\pi = (\pi_1, \dots, \pi_T)$, where π_t is an element of the set \mathcal{C} including characters and blank ($|\mathcal{C}| = 27$). After trained with CTC loss, \mathbf{P}_c becomes a precise indicator of phonetically important frames. To utilize this property, we tried to transform \mathbf{P}_c into the soft VAD [23] posteriors. However, there were problems that the shape of probabilities is too spiky so most of frames are ignored and the blank indicates not only non-speech frames but also the repetition of the previous character. So we add 1-layer bi-directional LSTM module (LSTM_c) to make the distribution more smoother. The LSTM has $|\mathcal{C}|$ states followed by 1-dimensional projection and sigmoid activation. We call the output vector $\mathbf{v}_c \in \mathbb{R}^T$ as *CTC-based soft VAD posteriors*.

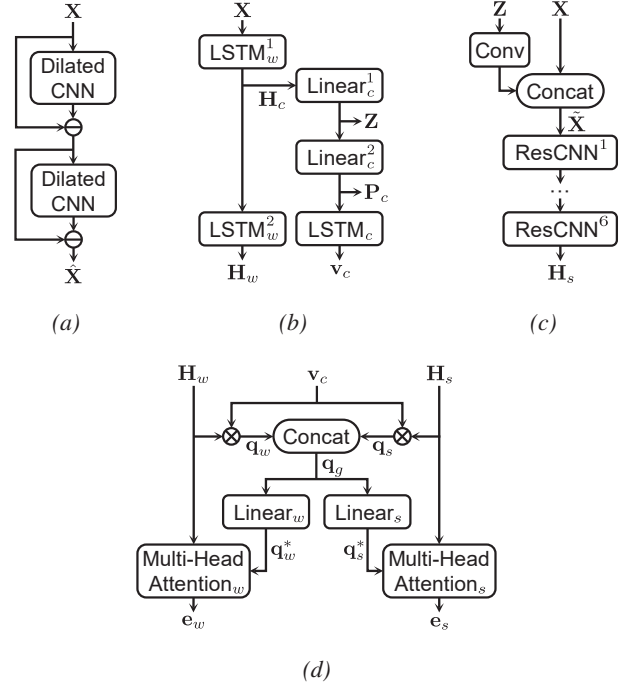


Figure 2: Detailed structures of sub-networks: (a) Enhancement network, (b) acoustic feature extraction network, (c) speaker feature extraction network, and (d) pooling network.

2.3. Speaker Feature Extraction Network

We use the bottleneck states \mathbf{Z} of Eq. 1 as phonetic conditional vectors. To adjust domain mismatch between phonetic and speaker domains, \mathbf{Z} enters one convolution layer (Conv in Fig. 2. (c)), being augmented to 3-channel. We concatenate it with $\hat{\mathbf{X}}$ and get a phonetically conditioned feature vectors $\tilde{\mathbf{X}} \in \mathbb{R}^{4 \times T \times 256}$. The advantage of the phonetic conditioning is that the network can have more knowledge of input speech [24] even in the short-duration condition so that it becomes easier to suppress unnecessary phonetic variations. The rest of the network consists of 6 modified version of ResNet [25], denoted as ResCNN^ℓ ($\ell=1, \dots, 6$). Each module has one convolution layer and two residual blocks as described in Tab. 1. Since we want to get frame-level speaker information, we does not change the temporal shape. At the last average and transpose layer, the speaker feature vectors $\mathbf{H}_s \in \mathbb{R}^{T \times 256}$ are extracted.

2.4. Pooling Network

Here, we propose a novel pooling method with *global query attention*, that integrates all domain information at the query generation stage. The method is composed of 4 steps, computing temporary queries with CTC-based soft VAD, global query generation, recomputing mutually informed domain queries, and aggregation. The temporary queries \mathbf{q}_w and \mathbf{q}_s in Eq. 3 are average representatives corresponding to phonetically relevant speech frames. Specifically, these are results of weighted sum of feature vectors using \mathbf{v}_c as the frame-wise weights. Then we generate a global query \mathbf{q}_g by concatenating two temporary queries as:

$$\mathbf{q}_g = [\mathbf{q}_w, \mathbf{q}_s] = \left[\mathbf{H}_w^T \mathbf{v}_c, \mathbf{H}_s^T \mathbf{v}_c \right] \in \mathbb{R}^{d_w + d_s}. \quad (3)$$

Table 1: CNN parameters for the enhancement network and speaker feature extraction network. All convolution layers are followed by batch normalizations and ReLU activations. Notation: C- channel, K- kernel size, S- stride, and D- dilation.

Module	Output Size	C, K, S, D
Dilated CNNs	$1 \times T \times 256$	$16, (3 \times 3), 1, 1$ $[16, (3 \times 3), 1, 2] \times 3$ $1, (3 \times 3), 1, 2$
Conv	$3 \times T \times 256$	$3, (3 \times 3), 1, 1$
ResCNN ¹	$8 \times T \times 128$	$8, (3 \times 3), (1 \times 2), 1$ $[8, (3 \times 3), 1, 1] \times 2$ $8, (3 \times 3), 1, 1$
ResCNN ²	$16 \times T \times 64$	$16, (3 \times 3), (1 \times 2), 1$ $[16, (3 \times 3), 1, 1] \times 2$ $16, (3 \times 3), 1, 1$
ResCNN ³	$32 \times T \times 32$	$32, (3 \times 3), (1 \times 2), 1$ $[32, (3 \times 3), 1, 1] \times 2$ $32, (3 \times 3), 1, 1$
ResCNN ⁴	$64 \times T \times 16$	$64, (3 \times 3), (1 \times 2), 1$ $[64, (3 \times 3), 1, 1] \times 2$ $64, (3 \times 3), 1, 1$
ResCNN ⁵	$128 \times T \times 8$	$128, (3 \times 3), (1 \times 2), 1$ $[128, (3 \times 3), 1, 1] \times 2$ $128, (3 \times 3), 1, 1$
ResCNN ⁶	$256 \times T \times 4$	$256, (3 \times 3), (1 \times 2), 1$ $[256, (3 \times 3), 1, 1] \times 2$ $256, (3 \times 3), 1, 1$
	$T \times 256$	average, transpose

As a result, the global query contains not only both acoustic and speaker information of the input utterance but also phonetic information in that temporary queries are derived with phonetically originated weights \mathbf{v}_c .

Since the ratio at which the global query contributes to each domain is different, the global query goes through two linear layers in parallel (Linear_w and Linear_s in Fig. 2. (d)) to recompute mutually informed domain queries \mathbf{q}_w^* and \mathbf{q}_s^* .

We adopt the multi-head attention scheme [26] for the aggregation, where the key and value are same as the acoustic or speaker feature vectors and they are aggregated with the mutually informed domain query:

$$\mathbf{q}_k^* = \text{Linear}_k(\mathbf{q}_g) \in \mathbb{R}^{d_k}, \quad (4)$$

$$\mathbf{e}_k = \text{Multi-Head}_k(\mathbf{q}_k^*, \mathbf{H}_k, \mathbf{H}_k) \in \mathbb{R}^{d_k}, \quad (5)$$

where $k \in \{w, s\}$, $d_w = 512$, $d_s = 256$, and we employ 4 heads. The resulting two vectors \mathbf{e}_w and \mathbf{e}_s are the acoustic word embedding and speaker embedding, respectively.

2.5. Loss Function

As depicted in Fig. 1, we use 3 simple loss functions. Two L_2 constrained softmax losses [27] \mathcal{L}_w and \mathcal{L}_s are used for KWS and SV, where $\|\mathbf{e}_w\| = 6$ and $\|\mathbf{e}_s\| = 12$, and \mathcal{L}_c is the CTC loss. The overall training loss is $\mathcal{L} = \mathcal{L}_w + \mathcal{L}_s + \mathcal{L}_c$. We do not use any explicit loss function for the enhancement purpose.

3. Experiments

3.1. Datasets

We use Google’s Speech Commands dataset V2 [28] which consists of 105829 utterances of 35 words spoken by 2618 speakers. All utterances have a duration of equal to or less than 1 s. We use only 2118 speakers, excluding those with less than 10 utterances. Then disjoint sets of 1959 and 159 speakers are randomly selected for training set and test set. Also, to check

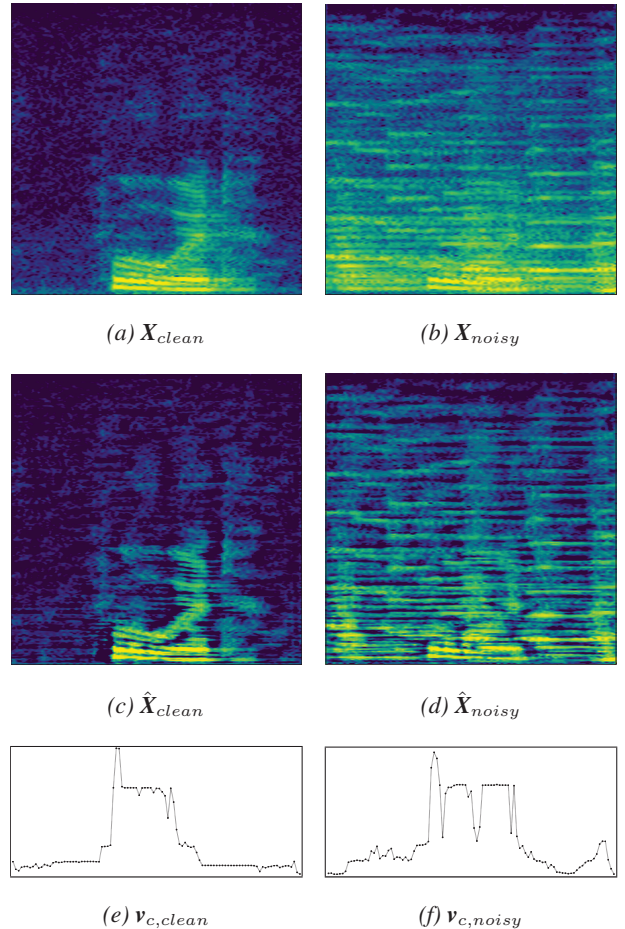


Figure 3: Visualization of one utterance in the test set. The first column is for clean speech and the second is for its corrupted version with Music noise at the SNR of 0 dB. (a)-(b): Original spectrograms. (c)-(d): Enhanced spectrograms. (e)-(f): CTC-based soft VAD posteriors. (Recommend viewing in color)

the robustness of KWS against unseen words, utterances corresponding to the three words ‘happy’, ‘marvin’, and ‘sheila’ are excluded from the training set.

Since the original dataset was collected using crowdsourcing, the dataset is not perfectly clean, but we regard it as the clean. For more challenging experiments, we corrupt the original dataset with the three types of noise, ‘Music’, ‘Babble’, and ‘Others’ from the MUSAN dataset [29]. For the training set, each utterance is augmented with a randomly selected type of noise under the SNR randomly chosen from the set $\{20, 10, 5, 0\}$ (in dB). For the test set, all types of noise and SNRs are considered, resulting in 13 environments.

3.2. Experiment Setting

All the networks are implemented with PyTorch [30]. We use the stochastic gradient descent with learning rate of 0.005 and momentum of 0.9 for the enhancement and speaker feature extraction networks. And the acoustic feature extraction and pooling networks are optimized by the Adam [31] with learning rate of 0.0005. The mini-batch size is set to 128 and two GTX 1080 Ti GPUs are used. The multi-task network is trained for 100 epochs and the model of the last epoch is used for evaluation.

Table 2: EER (%) results on the test set. (-) and (+) denote the exclusion and substitution for the ablation, respectively.

		Proposed		Baselines		(-) Enhancement network		(-) Phonetic conditioning		(-) Pooling network (+) Self-attention		(-) CTC	
Type	SNR	KWS	SV	KWS	SV	KWS	SV	KWS	SV	KWS	SV	KWS	SV
Clean		4.52	2.47	4.70	2.76	4.89	2.44	4.77	2.33	5.01	3.83	5.72	5.57
Music	20	4.72	4.24	4.91	6.15	5.45	4.63	5.00	4.51	5.22	6.05	5.94	6.45
	10	5.33	5.59	5.58	8.42	6.51	6.18	5.67	5.89	5.89	7.59	6.82	7.95
	5	6.40	6.97	6.64	10.25	7.99	7.81	6.79	7.28	7.04	9.28	8.29	9.83
	0	8.61	9.71	8.90	13.65	11.82	10.95	9.05	9.99	9.67	12.96	11.33	13.47
	Avg.	6.26	6.63	6.51	9.62	7.94	7.39	6.63	6.92	6.96	8.97	8.09	9.43
Babble	20	5.12	3.56	5.19	4.60	5.67	3.51	5.43	3.56	5.46	5.03	6.54	6.13
	10	6.67	4.61	6.92	6.32	7.98	4.63	7.16	4.63	7.55	6.33	8.70	7.66
	5	9.11	5.90	9.73	8.11	11.46	5.96	9.82	5.91	10.43	8.10	11.39	9.56
	0	14.57	8.81	15.42	12.15	18.47	8.81	15.92	8.63	16.51	12.41	16.87	13.64
	Avg.	8.87	5.72	9.31	7.80	10.89	5.73	9.58	5.68	9.98	7.97	10.87	9.25
Others	20	4.70	6.82	5.04	10.40	5.65	7.55	4.99	7.29	5.20	8.08	6.04	8.22
	10	5.39	9.64	5.70	13.58	6.73	10.81	5.64	10.54	5.84	10.46	6.69	10.86
	5	6.24	11.99	6.36	15.87	8.27	13.56	6.29	13.34	6.95	12.91	7.69	13.41
	0	8.00	15.81	8.26	19.44	11.66	18.18	8.09	18.16	9.03	17.45	9.84	17.73
	Avg.	6.08	11.06	6.34	14.82	8.08	12.52	6.25	12.33	6.75	12.22	7.56	12.55
Total Avg.		7.07	7.80	7.39	10.74	8.97	8.55	7.49	8.31	7.90	9.72	8.84	10.41

3.3. Evaluation Tasks and Metrics

Keyword spotting and speaker verification are basically discrimination tasks that make a decision given a score between embeddings of enrollment and test utterances. For both tasks, we use the cosine distance to measure the score and performances are evaluated using the equal error rate (EER). Here all utterances in the test set are used once for enrollment, one by one. Accordingly, 1 s - 1 s short-duration constraint is applied.

3.4. Baselines

For performance comparison, we use individually trained networks as the baselines of KWS and SV. For KWS baseline, the enhancement network and acoustic feature extraction network are used. This LSTM-based architecture has been used in [5, 7, 8]. Likewise, for SV baseline, the enhancement network and speaker feature extraction network are used without concatenating phonetic condition vectors \mathbf{Z} . The remaining network architecture is similar to the basic ResNet-based SV network [25]. To aggregate feature vectors, instead of the global query attention, we use the self-attention [32] method in Eq. 6 which has been widely used.

$$\mathbf{e}_k = \frac{1}{4} \sum_{h=1}^4 \text{Softmax} \left(\mathbf{v}_k^h \tanh \left(\mathbf{W}_k \mathbf{H}_k^T \right) \right) \mathbf{H}_k, \quad (6)$$

where $k \in \{w, s\}$, $\mathbf{W}_k \in \mathbb{R}^{128 \times d_k}$, and $\mathbf{v}_k^h \in \mathbb{R}^{128}$.

3.5. Results

In Tab. 2, we compare the performance on the test set between our proposed approach and baselines. Definitely, the proposed approach outperforms the baselines in all environments. For KWS, there is a slight increment of relatively 4.06% on average. However, for SV, we can obtain high improvements of relatively 26.71% on average and absolutely 2-4%. From this, we demonstrate that acoustic, phonetic, and speaker information can be fully utilized by joint learning the multi-task network.

In Fig. 3, we visualize example spectrograms and CTC-based soft VAD posteriors. We can observe that the enhancement network highlights the harmonics by reducing frequency components on valleys rather than eliminating noise itself, which can increase the frequency resolution of the spectrogram.

Also, noticeable noise reduction at the speech boundaries can be confirmed, which is clearly seen in Fig. 3. (c). Likewise, in Fig. 3. (d), there are narrow but deep divisions, particularly on the lower frequency region. When looking at \mathbf{v}_c , there are high posteriors on actual speech frames and it means that very meaningful temporary queries and global query can be generated at the global query attention.

In additional columns in Tab. 2, we investigate the effectiveness of the multi-task network with some ablation experiments. When the enhancement network is excluded, the results of KWS are particularly degraded on low SNRs. The exception of the phonetic conditioning shows the difference for SV performance on ‘Others’ noise type. It means that the phonetic information helps frame-level speaker feature extraction even with non-contextual noise. Meanwhile, the SV result in 0 dB ‘Babble’ indicates that mistaken phonetic information from background speech could make ambiguity. The next two columns show the global query attention performs better than the self-attention. Lastly, all the CTC related modules are removed, that is only the enhancement network is shared between two feature extraction networks. The results imply that the mutual contribution at the feature extractions and pooling network is equally or more effective than the existence of the enhancement network.

4. Conclusion

In this paper, we propose a multi-task network comprising multiple sub-networks. Also we introduce novel techniques of CTC-based soft VAD and global query attention to tightly utilize interrelated domain information even in challenging conditions of noisy environments, open-vocabulary KWS, and short-duration SV. Each sub-network is originally designed for individual purposes of enhancement, KWS, and SV, but great performance improvement can be achieved by effectively shared and mutually contributed. Experimental results demonstrate that the proposed approach outperforms the baselines.

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