MONOPHONE-BASED BACKGROUND MODELING FOR TWO-STAGE ON-DEVICE WAKE WORD DETECTION

Minhua Wu[1], *Sankaran Panchapagesan*[2*], *Ming Sun*[1], *Jiacheng Gu*[1]
Ryan Thomas[1], *Shiv Naga Prasad Vitaladevuni*[1], *Bjorn Hoffmeister*[1], *Arindam Mandal*[1]

[1]Amazon.com, Inc. USA [2*]Google LLC. USA

wuminhua@amazon.com, panchi@google.com, mingsun@amazon.com

ABSTRACT

Accurate on-device wake word detection is crucial to products with far-field voice control such as the Amazon Echo. It is quite challenging to build a wake word system with both low False Reject Rate (FRR) and low False Alarm Rate (FAR) in real scenarios where there are various types of background speech, music or noise, especially when computational resources on the device is limited. In this paper, we introduce a two-stage wake word system based on Deep Neural Network (DNN) acoustic modeling, propose a new way to model the non-keyword background events using monophone-based units and present how richer information can be extracted from those monophone units for final wake word detection. Under the new system, we could get around 16% relative reduction in FRR when fixing the false alarm level, and about 37% relative reduction in FAR on the other hand if we maintain the miss rate. For the 2nd stage classifier itself, it is able to reduce the false alarm rate relatively by about 67% on top of 1st stage hypothesis with very few computational resources.

Index Terms— wake word detection, deep neural network, monophone-based units

1. INTRODUCTION

The Amazon Echo is a smart home device using voice-based user interface. With the Keyword Spotting (KWS) system running on the device, it is always listening for the wake word, such as "Alexa". Once the wake word is detected, it can stream audio to cloud and interpret voice commands. For this application, wake word dectection is the first important step before interactions through distant speech recognition [1] and accurate on-device detection is crucially important for a great customer experience.

There is a rich literature on the topic of keyword spotting in continuous speech. In much of recent work, latency and computation are not concerns. Offline Large Vocabulary Continuous Speech Recognition (LVCSR) systems can be used to decode the audio and create transcripts or lattices, which can then be used for detecting the keyword(s) of interest [2] [3] [4] [5]. For online low-latency and computation-constrained KWS systems, Hidden Markov Models (HMM) were commonly used [6] [7] [8]. With the growing success of deep learning in recent years, Gaussian Mixture Models (GMM) for acoustic modeling under the HMM framework has been replaced with Deep Neural Network (DNN) in the field of Automatic Speech Recognition (ASR) [9]. This DNN-HMM hybrid approach using various neural network architecture has also been effectively applied for the wake word application [10][11][12][13][14]. Alternatively, some recent work proposed to build systems based on a single DNN or convolutional neural network (CNN) with no HMM involved [15] [16] [17]. RNN/LSTM based keyword spotting system has been proposed which can leverage longer temporal context [18] [19] [20] [21]. An end-to-end trained sequence-to-sequence model was also proposed recently [22]. There is no solid conclusion on whether the HMM-based KWS system is better than the non-HMM based system for real-time single wake word detection. Non-HMM based KWS system may have better discriminative capabilities, but it usually requires carefully designed post-smoothing algorithm to get the final decision. In this paper, we will focus on single wake word detection on resource-constrained embedded devices using HMM-based technique.

The wake word detector for experimentation in this paper has been designed to use a DNN-HMM decoder at first, followed by a light second stage classifier to make the final decision [23]. The small second stage classifier is meant to improve the discriminative power of the HMM-based KWS system without introducing too much computation and latency. The original system uses simple speech and non-speech events for background modeling. To better distinguish between the wake word and confusable background audio segments, we propose to incorporate monophone-based units to model the non-keyword background, and use those monophone statistics for further classification.

The paper is organized as follows. In section 2, we will briefly describe how the original two-stage wake word system works. In the next section, we will illustrate how we

[*] Work conducted while the author was at Amazon

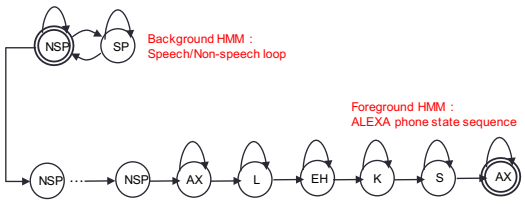


Fig. 1: *A simplified 1st stage HMM decoding graph for the wake word "Alexa"*

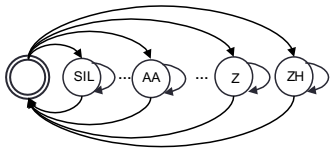


Fig. 2: *A simplified 1st stage monophone-based background HMM*

expand to use various phoneme-based events to model the background and how we can obtain richer features for final classification. Finally, we will compare performance of the baseline and the new system using monophone-based background modeling technique.

2. BASELINE TWO-STAGE WAKE WORD SYSTEM

2.1. 1st Stage DNN-HMM Decoder

An example 1st stage HMM decoding graph for the keyword "Alexa" is shown in Figure 1. Note that single-state HMMs for the phones are shown for simplicity. The foreground HMM consists of wake word phones and several non-speech frames at the beginning, while the background HMM consists of a loop over single-state speech and non-speech events. Viterbi decoding is performed on the HMM decoding graph using frames of acoustic features computed from the audio signal, and we are using a Deep Neural Network (DNN) based acoustic model to compute posteriors of different HMM states. A wake word is hypothesized by the first stage if the final state of the foreground HMM is reached and the difference between foreground and background log-likelihoods during the candidate segment exceeds a threshold. Various transition and exit penalties in both the foreground and background HMMs can be tuned for better accuracy, and a first stage DET curve can thus be obtained by plotting the lowest achievable FRR at a given FAR.

2.2. 2nd Stage Classifier

When the first stage log-likelihood ratio exceeds the threshold, the corresponding audio segment $\boldsymbol{X}$which runs through is treated as a candidate wake word. Though candidates triggered from the first stage will be of different durations, they will be transformed to a feature vector $\mathbf{v}$ of dimension D ($D = 67$) based on how the candidate segment is aligned with the foreground HMM and what are the likelihoods for frames in the candidate given different states. Specifically, the feature vector $\mathbf{v}$ for the candidate wake word $\boldsymbol{X}$ includes information from both the entire segment and individual phone segments. Segment-level features include the duration, keyword likelihood score, normalized likelihood score and posterior for the keyword. For the phone-level features, we consider absolute and relative phone duration, phone log-likelihood, averaged phone/speech confidence scores, local context features such as left/central/right phone confidence, and entropy based features according to context phone confidence scores. A second stage classifier is then trained based on feature vectors extracted from wake word candidates to make the final decision. We use a small feed-forward neural network for experimentation here. For the consideration of detection latency, we are not using RNN based architecture or attention mechanism to summarize the information, but it could be tried in the future.

3. NEW WAKE WORD SYSTEM USING MONOPHONE-BASED BACKGROUND MODELING

3.1. 1st Stage DNN-HMM Decoder with Monophone-based Background Model

Instead of simply using speech and non-speech background events, we expand them to various monophones. With these new units introduced, our new background HMM becomes a phone-level unigram FST. Figure 2 is a simplified version of the new background model, since we are actually using 3-state HMM topology for these background monophones. We should still be able to use Viterbi decoding and DNN based acoustic model on the new decoding graph, but output targets of the DNN will be expanded accordingly.

3.2. New Feature Engineering for 2nd Stage Classifier

Since we now have a first stage wake word detector with more HMM states, we can extract richer information from them for better second verification. The original 67 feature dimensions illustrated in section 2.2 are still valid. Additionally, we come up with a new score ($MatchScore_{p,q}$) measuring the degree of match between each candidate's wake word phone segment p and every background monophone q, as indicated in equation 1. For each frame X_t within one wake word phone p, we take the maximum log likelihood among the three states of each background monophone q, and average these log likelihoods over the phone duration of p. We need to compute the match score for each wake word phone p with respect to every background monophone q. Since the background model is only learned from non-keyword audio, we would expect lower

match score between the real wake word phone segment and background monophones, but higher match score between phone segment in false wake word hypothesis and background monophones. In this case, we could be able to distinguish better between real wake words and confusable segments among first stage candidates by introducing these new features. We are using $N_q = 44$ monophone units in the background model, so we could introduce 44 extra features for each wake word phone segment. Therefore, the new second stage classifier will end up with using a new feature vector of dimension 375 ($67 + 7 \times 44$). We could do feature selection to make the model work more efficiently, but this topic is not discussed under the scope of this paper.

$$MatchScore_{p,q} = \frac{1}{Dur_p} \sum_{t=T_p}^{T_{p+1}-1} max\{log(P(X_t|Q_q^L,\theta_{BG})), log(P(X_t|Q_q^C,\theta_{BG})), log(P(X_t|Q_q^R,\theta_{BG}))\} \quad (1)$$

$p \in$ wake word phones:
$\{SIL_{Preceding}, AX\_B_{Alexa}, L_{Alexa}, EH_{Alexa}, K_{Alexa}, S_{Alexa}, AX\_E_{Alexa}\}$
$q \in$ background monophones

4. EXPERIMENT RESULTS

4.1. Baseline Setup

The training data used in this work consists of several thousand hours of the real far-field data captured in various rooms. It contains approximately several hundred thousand subjects. Our development and test set contain tens of thousands of speech streams uttered by hundreds of subjects. Both the development and test set have approximately 30,000 wake word instances. We use a feed-forward DNN acoustic model in the first stage. The decoding graph consists of a foreground wake word HMM and a background speech/non-speech loop HMM. The input acoustic features to the DNN consists of 31 stacked frames of 20-dimensional Log mel-Filter-Bank Energies (LFBE) features (20 frames for left context and 10 frames for right context). The baseline DNN has 50 output targets corresponding to phoneme states under wake words, commands (e.g. "STOP") and speech/non-speech events. The DNN acoustic model is at the same time trained to predict the Large Vocabulary Continuous Speech Recognition (LVCSR) targets, since this is known to improve the accuracy for wake word detection [10]. A weighted cross-entropy objective function is used where the loss stream corresponding to the LVCSR task is weighted by 0.1 while the loss stream corresponding to the wake word task is weighted by 0.9. Each wake word candidate segment hypothesized from the first stage is then transformed to a fixed 67-dimensional feature vector for final detection with the second stage classifier using a small feedforward neural network (NN). The feed-forward DNN acoustic model is chosen to have 4 hidden layers. Two sizes for the hidden layer are tried (896, 1024) respectively in the experiments. The GPU-based distributed DNN trainer described in [24] is utilized and the DNN is discriminatively pre-trained beforehand in a layer-wise manner [25] on a small subset of the training data.

4.2. Monophone-based System Setup

For the decoding graph in the new wake word system using monophone-based background, the foreground wake word HMM keeps the same, but the background HMM changes to be a phone-level unigram FST as plotted in figure 2 from section 3.1. Input features to the DNN acoustic model are still the same but wake word targets at the output layer are expanded. Non-keyword frames in the training data are now assigned with specific monophone states instead of either speech or non-speech label. The new DNN now has 178 output nodes including both wake word phone states and monophone states for the wake word task. Each keyword candidate segment is then transformed to a fixed 375-dimensional feature vector for the 2nd stage NN classifier.

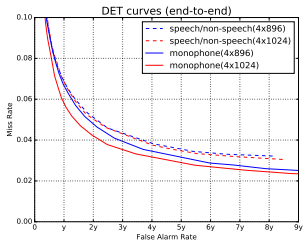
4.3. Experiment Results

4.3.1. 1st Stage HMM Tuning

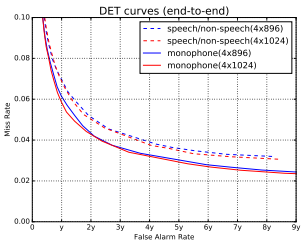
We first tune the two systems by varying penalties on the decoding graph. It turns out performance of the two systems are almost the same at this stage on the dev set. This is expected since both the baseline and the new system model foreground and background phones, and the new system is not using higher order language model but phone-level unigram. However, we can extract richer information from the new system's first stage decoding results for further classification. For both the baseline and the new wake word system, we choose a first stage operating point under the similar level of recall at around 0.02 and proceed to build the second stage classifier.

4.3.2. End-to-end Evaluation

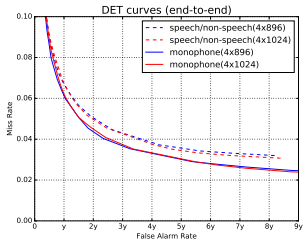
DET curves comparing the end-to-end performance of the two systems are displayed in figure 3. We tried several sizes for hidden layers of the 2nd stage NN classifier with two hidden layers. These curves are obtained by sweeping the final accept threshold in each system. The dashed curve corresponds to the overall performance of the baseline wake word system, and the solid curve corresponds to the overall performance of the new wake word system using monophone-based background model. We can see the new system performs generally better than the baseline, which indicates the additional features derived from the new wake word system are effectively helpful. When we vary the size for hidden layers of the 2nd stage NN classifier (from figure 4a to 3d), we can see some gain when changing



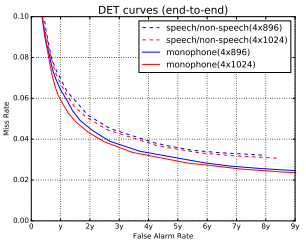
(a) *2×32 for 2nd stage NN*



(b) *2×64 for 2nd stage NN*

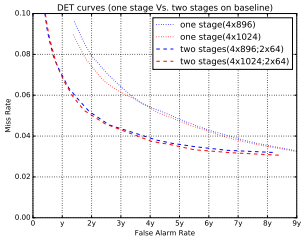


(c) *2×128 for 2nd stage NN*

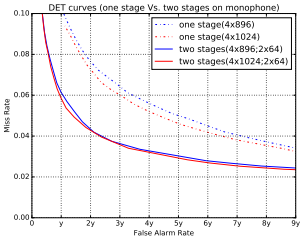


(d) *2×256 for 2nd stage NN*

Fig. 3: *End-to-end comparison of the baseline wake word system and the new system using monophone-based background modeling; DET curves on test set; Axis of the false alarm rate is obscured due to the sensitive nature of this information*



(a) *speech/non-speech*



(b) *monophone*

Fig. 4: *Comparision of the performance with and without 2nd stage classifier (2×64 NN); DET curves on test set; Axis of the false alarm rate is obscured due to the sensitive nature of this information*

from 32 hidden units to 64 hidden units on the 4×896 new wake word system, but we don't see much big difference on other cases. In this case, we will use the 2×64 2nd stage NN for the following illustration. Table 1 summarizes performance and number of parameters in various wake word systems. When transiting from the 4×896 speech/non-speech background based wake word system to the 4×896 monophone background based wake word system, we can achieve about 16% relative reduce in terms of false reject rate (FRR) when the false alarm rate (FAR) is fixed at around 2y, and we can on the other hand reduce the FAR by about 37% relatively if we maintain the FRR to be around 0.04 with similar amount of parameters. If we instead transit to use the 4×1024 speech/non-speech background based wake word system, it will introduce about 27% percent more parameters but the gain is much smaller. By further increasing the first stage DNN size from 4×896 to 4×1024, the relative reductions in FRR and FAR are quite small by less than 3%.

Table 1: *Summary of different wake word systems*

	2^{nd} NN: 2x64		
	FRR (fix FAR=2y)	FAR (fix FRR=0.04)	Params
SP/NSP(4×896)	0.051	3.71y	3.02M
SP/NSP(4×1024)	0.050	3.43y	3.84M
monophone(4×896)	0.043	2.35y	3.15M
monophone(4×1024)	0.042	2.31y	3.99M

4.3.3. Effectiveness of the 2nd stage

Figure 4 compares performance with and without the 2nd stage classifier on both the baseline and the new system. It turns out that if we fix the false reject rate to be at 0.04, we could reduce the FAR by about 45% relatively by deploying the 2nd stage classifier for the 4×896 speech/non-speech background based wake word system. The 2nd stage classifier seems to be more effective for the monophone background based wake word system. We can achieve about 67% relative reduction in FAR using the 2nd stage classifier for the 4×896 monophone background based wake word system. Apart from the accuracy gain, computational resources required by the 2nd stage classifier is very cheap compared to the 1st stage. Its size is more than 100 times smaller than the 1st stage model and there is no need to run Viterbi decoding on a restricted graph.

5. CONCLUSION

In this paper, we introduce a two-stage wake word system. We propose a different way to model the non-keyword background audio by expanding the speech/non-speech events to more specific monophone-based units at the first stage and we also present how to extract richer features for a second stage verification. By using the new wake word system, we can reduce FRR by about 16% relatively when the false alarm level is maintained, and we are able to reduce FAR by about 37% relatively if we maintain the level of miss rate. We also demonstrate effectiveness of the second stage classifier itself. It is able to reduce the FAR by about 67% relatively on top of 1st stage hypothesis with very few computational resources. In the future, it is worthwhile to apply sequence-discriminative training [26] [27] which is widely used in the field of LVCSR to train the wake word acoustic model, since we could now have rich phoneme-based information in the lattice.

6. REFERENCES

[1] Kenichi Kumatani, John McDonough, and Bhiksha Raj, "Microphone array processing for distant speech recognition: From close-talking microphones to far-field sensors," *IEEE Signal Processing Magazine*, vol. 29, no. 6, pp. 127–140, 2012.

[2] David RH Miller, Michael Kleber, Chia-Lin Kao, Owen Kimball, Thomas Colthurst, Stephen A Lowe, Richard M Schwartz, and Herbert Gish, "Rapid and accurate spoken term detection," in *Eighth Annual Conference of the International Speech Communication Association*, 2007.

[3] Siddika Parlak and Murat Saraclar, "Spoken term detection for turkish broadcast news," in *Acoustics, Speech and Signal Processing, 2008. ICASSP 2008. IEEE International Conference on*. IEEE, 2008, pp. 5244–5247.

[4] Guoguo Chen, Oguz Yilmaz, Jan Trmal, Daniel Povey, and Sanjeev Khudanpur, "Using proxies for oov keywords in the keyword search task," in *Automatic Speech Recognition and Understanding (ASRU), 2013 IEEE Workshop on*. IEEE, 2013, pp. 416–421.

[5] Stavros Tsakalidis, Roger Hsiao, Damianos Karakos, Tim Ng, Shivesh Ranjan, Guruprasad Saikumar, Le Zhang, Long Nguyen, Richard Schwartz, and John Makhoul, "The 2013 bbn vietnamese telephone speech keyword spotting system," in *Acoustics, Speech and Signal Processing (ICASSP), 2014 IEEE International Conference on*. IEEE, 2014, pp. 7829–7833.

[6] Richard C Rose and Douglas B Paul, "A hidden markov model based keyword recognition system," in *Acoustics, Speech, and Signal Processing, 1990. ICASSP-90., 1990 International Conference on*. IEEE, 1990, pp. 129–132.

[7] Jay G Wilpon, Lawrence R Rabiner, C-H Lee, and ER Goldman, "Automatic recognition of keywords in unconstrained speech using hidden markov models," *IEEE Transactions on Acoustics, Speech, and Signal Processing*, vol. 38, no. 11, pp. 1870–1878, 1990.

[8] JG Wilpon, LG Miller, and P Modi, "Improvements and applications for key word recognition using hidden markov modeling techniques," in *Acoustics, Speech, and Signal Processing, 1991. ICASSP-91., 1991 International Conference on*. IEEE, 1991, pp. 309–312.

[9] Geoffrey Hinton, Li Deng, Dong Yu, George E Dahl, Abdel-rahman Mohamed, Navdeep Jaitly, Andrew Senior, Vincent Vanhoucke, Patrick Nguyen, Tara N Sainath, et al., "Deep neural networks for acoustic modeling in speech recognition: The shared views of four research groups," *IEEE Signal Processing Magazine*, vol. 29, no. 6, pp. 82–97, 2012.

[10] Sankaran Panchapagesan, Ming Sun, Aparna Khare, Spyros Matsoukas, Arindam Mandal, Björn Hoffmeister, and Shiv Vitaladevuni, "Multi-task learning and weighted cross-entropy for dnn-based keyword spotting," *Interspeech 2016*, pp. 760–764, 2016.

[11] Ming Sun, David Snyder, Yixin Gao, Varun Nagaraja, Mike Rodehorst, Sankaran Panchapagesan, Nikko Strom, Spyros Matsoukas, and Shiv Vitaladevuni, "Compressed time delay neural network for small-footprint keyword spotting," *Proc. Interspeech 2017*, pp. 3607–3611, 2017.

[12] Ming Sun, Andreas Schwarz, Minhua Wu, Nikko Strom, Spyros Matsoukas, and Shiv Vitaladevuni, "An empirical study of cross-lingual transfer learning techniques for small-footprint keyword spotting," *Machine Learning and Applications (ICMLA), 2017 16th IEEE International Conference on*, pp. 255–260, 2017.

[13] Kenichi Kumatani, Sankaran Panchapagesan, Minhua Wu, Minjae Kim, Nikko Strom, Gautam Tiwari, and Arindam Mandal, "Direct modeling of raw audio with dnns for wake word detection," in *IEEE Automatic Speech Recognition and Understanding Workshop (ASRU) December 16-20, 2017*, 2017.

[14] Jinxi Guo, Kenichi Kumatani, Ming Sun, Minhua Wu, Anirudh Raju, Nikko Strom, and Arindam Mandal, "Time-delayed bottleneck highway networks using a dft feature for keyword spotting," *Acoustics, Speech and Signal Processing (ICASSP), 2018 IEEE International Conference on*, 2018.

[15] Guoguo Chen, Carolina Parada, and Georg Heigold, "Small-footprint keyword spotting using deep neural networks," in *Acoustics, Speech and Signal Processing (ICASSP), 2014 IEEE International Conference on*. IEEE, 2014, pp. 4087–4091.

[16] Tara N Sainath and Carolina Parada, "Convolutional neural networks for small-footprint keyword spotting.," in *INTERSPEECH*, 2015, pp. 1478–1482.

[17] George Tucker, Minhua Wu, Ming Sun, Sankaran Panchapagesan, Gengshen Fu, and Shiv Vitaladevuni, "Model compression applied to small-footprint keyword spotting.," in *INTERSPEECH*, 2016, pp. 1878–1882.

[18] Santiago Fernández, Alex Graves, and Jürgen Schmidhuber, "An application of recurrent neural networks to discriminative keyword spotting," in *International Conference on Artificial Neural Networks*. Springer, 2007, pp. 220–229.

[19] Martin Woellmer, Bjoern Schuller, and Gerhard Rigoll, "Keyword spotting exploiting long short-term memory," *Speech Communication*, vol. 55, no. 2, pp. 252–265, 2013.

[20] Pallavi Baljekar, Jill Fain Lehman, and Rita Singh, "Online word-spotting in continuous speech with recurrent neural networks," in *Spoken Language Technology Workshop (SLT), 2014 IEEE*. IEEE, 2014, pp. 536–541.

[21] Ming Sun, Anirudh Raju, George Tucker, Sankaran Panchapagesan, Gengshen Fu, Arindam Mandal, Spyros Matsoukas, Nikko Strom, and Shiv Vitaladevuni, "Max-pooling loss training of long short-term memory networks for small-footprint keyword spotting," in *Spoken Language Technology Workshop (SLT), 2016 IEEE*. IEEE, 2016, pp. 474–480.

[22] Yanzhang He, Rohit Prabhavalkar, Kanishka Rao, Wei Li, Anton Bakhtin, and Ian McGraw, "Streaming small-footprint keyword spotting using sequence-to-sequence models," *arXiv preprint arXiv:1710.09617*, 2017.

[23] Ming Sun, Varun Nagaraja, Björn Hoffmeister, and Shiv Vitaladevuni, "Model shrinking for embedded keyword spotting," in *Machine Learning and Applications (ICMLA), 2015 IEEE 14th International Conference on*. IEEE, 2015, pp. 369–374.

[24] Nikko Strom, "Scalable distributed dnn training using commodity gpu cloud computing.," in *INTERSPEECH*, 2015, vol. 7, p. 10.

[25] Frank Seide, Gang Li, Xie Chen, and Dong Yu, "Feature engineering in context-dependent deep neural networks for conversational speech transcription," in *Automatic Speech Recognition and Understanding (ASRU), 2011 IEEE Workshop on*. IEEE, 2011, pp. 24–29.

[26] Karel Veselỳ, Arnab Ghoshal, Lukás Burget, and Daniel Povey, "Sequence-discriminative training of deep neural networks.," in *Interspeech*, 2013, pp. 2345–2349.

[27] Daniel Povey, Vijayaditya Peddinti, Daniel Galvez, Pegah Ghahrmani, Vimal Manohar, Xingyu Na, Yiming Wang, and Sanjeev Khudanpur, "Purely sequence-trained neural networks for asr based on lattice-free mmi," *Submitted to Interspeech*, 2016.