ALMOST ZERO-RESOURCE ASR-FREE KEYWORD SPOTTING USING MULTILINGUAL BOTTLENECK FEATURES AND CORRESPONDENCE AUTOENCODERS

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ABSTRACT

We compare features for dynamic time warping based keyword spotting in an almost zero-resource setting. The objective is to support United Nations (UN) humanitarian relief efforts in parts of Africa with severely under-resourced languages. As supervised resource, we restrict ourselves to an easily-compiled small set of isolated keywords. For feature extraction, we integrate a multilingual bottleneck feature extractor (BNF), trained on well-resourced out-of-domain languages, with a correspondence autoencoder (CAE), trained on extremely sparse in-domain data. We find that, on their own, BNFs and CAE features achieve more than 2% absolute performance improvement over baseline MFCCs. However, by using BNFs as input to the CAE, even better performance is achieved, with an 11% absolute improvement in ROC AUC over MFCCs and twice as many top-10 retrievals. We conclude that integrating BNFs with the CAE allows both large out-of-domain and sparse in-domain resources to be exploited for improved ASR-free keyword spotting.

Index Terms—Keyword spotting, low-resource speech processing, multilingual features, correspondence autoencoder, zero-resource speech technology.

1. INTRODUCTION

In Uganda, internet infrastructure is often poorly developed, precluding the use of social media to gauge sentiment. Instead, community radio phone-in talk shows are used to voice views and concerns. In a project piloted by the United Nations (UN), radio-browsing systems have been developed to monitor such radio shows [1, 2]. Currently, these systems are actively and successfully supporting relief and developmental programmes by the organisation. However, the deployed radio-browsing systems use automatic speech recognition (ASR) and are therefore highly dependent on the availability of substantial transcribed speech corpora in the target language. This has proved to be a serious impediment when quick intervention is required, since the development of such a corpus is always time-consuming.

In a conventional keyword spotting system, where a speech database is searched for a set of keywords, ASR is used to generate lattices which are in turn searched for the presence or absence of keywords [3, 4]. In resource-constrained settings where ASR is not available and cannot be developed, ASR-free keyword spotting approaches become attractive, because these are developed without substantial labelled data [5–10].

One approach to ASR-free keyword spotting is to extend query-by-example search (QbE), where the search query is provided as audio rather than a written keyword. QbE can be performed by using dynamic time warping (DTW) to perform a direct match between a search query and utterances in the search collection [11–14]. To perform keyword spotting via QbE, a number of labelled spoken keyword instances can be used as templates. Each template keyword is used as a query with which DTW-based QbE is performed. Since the class of each template is known, the individual per-exemplar QbE results can be aggregated to determine whether a given written keyword occurs in a particular utterance. The advantage is that this technique only requires a set of labelled keywords, and can therefore be implemented using a dataset that can be much smaller than that required to train a full classifier-based ASR-based keyword spotter [6, 7].

Recent interest in zero-resource QbE has led researchers to consider the use of different features [15–20]. Multilingual bottleneck feature (BNF) extractors trained on well-resourced but out-of-domain languages have been shown to improve on the performance of MFCCs in a number of studies [21–29].

Our goal is to improve DTW-based keyword spotting by combining the advantages of using labelled resources from well-resourced languages for learning features, with the advantage of fine-tuning on a very sparse labelled data in the target low-resource language. For fine-tuning on target data, we use the correspondence autoencoder (CAE), a model originally developed for the zero-resource setting where only unlabelled data is available [30, 31]. As target language data, we use a small number of labelled isolated keywords that can be easily and quickly gathered. By learning a mapping between all possible combinations of alternative utterances of the same keyword type, the idea is that the CAE can learn to normalise...
out aspects not common to the keywords (e.g. speaker, gender, channel), while capturing aspects that are (e.g. word identity). We benchmark CAE features against MFCCs and BNFs. We show that when a CAE is trained on top of BNFs, we achieve the best keyword spotting results, indicating that multilingual feature extraction and target-language fine-tuning can be complementary.

2. RADIO BROWSING SYSTEM

The UN radio browsing system is shown in Figure 1. The existing system, shown in the top block in the figure, uses ASR to decode the audio, producing lattices that are searched for keywords. Human analysts filter the detected keywords and their meta-data is compiled into a structured, categorised and searchable format. The ASR-free system (bottom block) bypasses the ASR and lattice search and instead detects occurrences of the keywords directly from incoming audio [6, 7]. High false positive rates of the keyword spotter can be accommodated due to the presence of the human analysts, and the output of the system as a whole has been in continuous successful operation for several months. A more detailed discussion on the role of human analysts and examples of detected topics of interest have been presented in [2].

![Figure 1: The United Nations (UN) radio browsing system.](image)

3. DATA

As search data in our experiments, we used a 23-hour English corpus of South African Broadcast News (SABN) [32]. Since transcriptions are available for this data, it allows system performance to be experimentally evaluated. However, in all other respects we consider the SABN data as untranscribed. Ultimately our goal is to apply this system to truly low-resource languages, and English is used here as a proxy on which we can perform extensive evaluation. Table 1 shows how the corpus is split into training, development and test sets.

For training our keyword spotter, we use a small disjoint corpus of 40 isolated keywords, each uttered twice by 24 South African speakers (12 male, 12 female). The resulting set of 1920 isolated keyword utterances represents the only labelled in-domain data our keyword spotter uses for training. There is no speaker overlap with the SABN dataset, which we treat exclusively as search data. The definite mismatch between the datasets is intentional as it reflects the probable operational setting of the radio browsing system.

4. DYNAMIC TIME WARPING BASED KEYWORD SPOTTING

Dynamic time warping (DTW) is an appropriate approach to keyword detection when only a few isolated exemplars of keywords are available because it requires as little as a single audio template. DTW aligns two time series, represented as feature vector sequences, by warping the relative time axis iteratively until an optimal match is found.

For DTW-based keyword spotting, features are extracted for both the keyword exemplar and the search utterance in which the keyword is to be detected. In our straightforward implementation, the keyword exemplar is slid progressively over the search utterance, and at each step DTW computes the alignment cost between the keyword and the portion of the utterance under alignment. Using a step of 3 frames, the overall best alignment for each search utterance is determined and taken as a score indicating how likely it is that the search utterance contains the keyword. Since we have more than one exemplar of the same keyword type, the best score across all templates of the same keyword type is used. By applying an appropriate threshold to this score, a decision can be taken regarding the presence or absence of the keyword in each search utterance. More refined DTW-based search approaches have been proposed [11-14], but here we restrict ourselves to this straightforward implementation.

5. NEURAL NETWORK FEATURE EXTRACTION

We investigate different types of input features for our DTW-based keyword spotter. While transcribed in-domain data is difficult, time-consuming and expensive to compile, untranscribed in-domain speech audio data is much easier to obtain in substantial quantities. We investigate the use of autoencoders (§5.1) and correspondence autoencoders (§5.2) as a means of taking advantage of such untranscribed data (with the latter also requiring a sparse set of labelled examples in the target language). In addition, although large amounts of transcribed

| Set       | Utterances | Speech (h) |
|-----------|------------|------------|
| Train     | 5231       | 7.94       |
| Development | 2988   | 5.37       |
| Test      | 5226       | 10.33      |
| Total     | 13 445     | 23.64      |

Table 1: The South African Broadcast News (SABN) dataset.

1Examples available at [http://radio.unglobalpulse.net](http://radio.unglobalpulse.net)
in-domain speech data may not be available, large annotated speech resources do exist for several well-resourced languages. These datasets can be used to train multilingual bottleneck feature extractors (§5.3).

5.1. Autoencoder Features

An autoencoder (AE) is a feedforward neural network trained to reconstruct its input at its output. A single-layer AE consists of an input layer, a hidden layer and an output layer. The AE takes input \(x \in \mathbb{R}^D\) and maps it to a hidden representation \(h = \sigma(W^{(0)}x + b^{(0)})\), with \(\sigma\) denoting a non-linear activation (we use \text{tanh}). The output of the AE is obtained by decoding the hidden representation: \(y = \sigma(W^{(1)}h + b^{(1)})\). The network is trained to reconstruct the input using the loss \(||x - y||^2\).

A stacked AE \([33]\) is obtained by stacking several AEs, each AE-layer taking as input the encoding from the layer below it. The stacked network is trained one layer at a time, each layer minimizing the loss of its output with respect to its input. A number of studies have found that hidden representations from an intermediate layer in such a stacked AE are useful as features in speech applications \([30,33,38]\).

Here we train a 8-layer stacked AE feature extractor on the training portion of the SABN corpus (transcriptions are disregarded). 39-dimensional MFCCs consisting of 13 cepstra, delta and delta-delta coefficients are used as input. All layers have 100 hidden units, apart from the penultimate layer which has 39 units. This layer the features used down-stream.

5.2. Correspondence Autoencoder

While an AE is trained using the same speech frames as input and output, a correspondence autoencoder (CAE) uses frames from different instances of the same word as input and output. Using the set of isolated keywords, we consider all possible pairs of words of the same type. For each pair, DTW is used to find the minimum-cost frame-level alignment between the two words, as illustrated in Figure 2. Individual aligned frame pairs are then used as input-output pairs to the CAE. The CAE is therefore trained on pairs of speech features \((x^{(a)}, x^{(b)})\), where \(x^{(a)}\) would be a frame from one word, and \(x^{(b)}\) would be the frame from another word (of the same type as the first). Given input \(x^{(a)}\), the output of the network \(y\) is then trained to minimise the CAE loss \(||y - x^{(b)}||^2\), as shown in Figure 2.

To obtain useful features, it was found that it is essential to first pretrain the CAE as a conventional AE \([30]\). Here, our CAE has the same structure as the AE in the previous section. Again output features are extracted from the penultimate 39-dimensional layer. We first pretrain the CAE as an AE on the untranscribed SABN training dataset. This network is then fine-tuned on the set of isolated keywords using the CAE loss described above. The CAE therefore takes advantage of a large amount of untranscribed data for initialisation, and then combines this with a weak form of supervision on a small amount of labelled data.

5.3. Bottleneck Features

Multilingual bottleneck feature (BNF) extractors trained on a set of well-resourced languages have been shown to perform well in a number of studies \([7,21–29]\), and can be applied directly in an almost-zero-resource setting. BNFs are obtained by training a deep neural network jointly on transcribed data from multiple languages. The lower layers of the network are shared among all languages. The output layer has phone or HMM state labels as targets and may also be shared or may be split into separate parts for each language. The layer directly preceding the output layer often has a lower dimensionality than the preceeding layers, because it should capture aspects that are common to all the languages. This has led to the term ‘bottleneck’.

Different neural network architectures can be used to obtain BNFs. We use time-delay neural networks (TDNNs), specifically a 6-layer TDNN from \([21]\) trained on 10 languages from the GlobalPhone corpus. The network uses ReLU activations and batch normalisation, with a 39-dimensional bottleneck layer. 40-dimensional high resolution MFCCs appended with 100-dimensional i-vectors for speaker adaptation are used as inputs to the network.

6. EXPERIMENTS

6.1. Experimental Setup

In addition to MFCCs, we use each of the neural networks above \([33]\) as feature extractors, using features from the inter-
medium/bottleneck layers of the CAE, AE and BNF as input to our DTW-based keyword spotter \cite{5}. All the neural networks take MFCCs as input. Each takes advantage of resources in a particular way: the AE is trained on untranscribed target-language data; the CAE is initialised on untranscribed data and then fine-tuned on a small amount of labelled target-language data; and the BNFs use larger amounts of labelled non-target-language data. We are also interested to know whether these approaches are complimentary. To test this, we perform experiments in which the AE and CAE are trained with BNFs rather than MFCCs as input. Hyperparameters for the CAE were taken directly from \cite{10}, i.e., no tuning was performed on the development set, so it can be considered a second test set.

Keyword spotting performance is assessed using a number of standard metrics. The receiver operating characteristic (ROC) is obtained by plotting the false positive rate against the true positive rate as the keyword detection threshold is varied. The area under this curve (AUC) is used as a single metric across all operating points. The equal error rate (EER) is the point at which the false positive rate equals the false negative rate (thus, lower EER is better). Precision at 10 (P@10) and precision at N (P@N) are the proportion of correct keyword detections among the top 10 and top N hits, respectively.

### 6.2. Results

Keyword spotting results are presented in Table \ref{tab:results}. The column headings AE\textsubscript{MFCC}/CAE\textsubscript{MFCC} and AE\textsubscript{BNF}/CAE\textsubscript{BNF} are used to distinguish between networks trained using MFCCs and BNFs as input features. Comparing the MFCC, AE\textsubscript{MFCC} and CAE\textsubscript{MFCC} results, we see that, while the AE does not seem to provide any benefit, the CAE consistently outperforms the MFCC baseline. We also see that the BNF and CAE\textsubscript{MFCC} result are similar for both the development and test data. Using a small amount of labelled data in a target language can therefore be just as beneficial as using large amounts of labelled data from several non-target languages for feature learning. This may be important in situations where large out-of-domain datasets are not available.

Our best overall model on both the development and test data is the CAE\textsubscript{BNF}. This is the CAE trained with BNFs as input. Both P@10 and P@N are close to double the scores of the closest competitor on both sets, while AUC is around 7% and EER around 10% better than standard BNFs. Compared to the baseline MFCCs, AUC and EER improve by more than 11% when using the CAE\textsubscript{BNF} features. The AE\textsubscript{BNF} also achieves improvements over its MFCC-counterpart, but not to the same degree as CAE\textsubscript{BNF}. The CAE\textsubscript{BNF} shows the benefits of incorporating features learned from well-resourced non-target languages with fine-tuning on a small amount of labelled target-language data after pretraining on untranscribed in-domain speech.

Our findings here are similar to those of \cite{21,22}. There, a CAE trained on BNFs using a larger number of ground truth word pairs outperformed the individual methods in intrinsic evaluations. This improvement, however, does not hold consistently when automatically discovered word segments were used (in which case the CAE is completely unsupervised). Our results here show that, even when the number of true utterances is relatively small, consistent improvements can be obtained by combining BNFs and the CAE. We show this directly in an extrinsic down-stream keyword spotting task.

### 7. Conclusion

We investigated the use of different neural network features for improving ASR-free DTW-based keyword spotting in an almost zero-resource setting. The only labelled data used were a small number of isolated keyword utterances. Features were extracted using a multilingual bottleneck network (BNF), a stacked autoencoder (AE) and a correspondence autoencoder (CAE). We also considered combining these, feeding the AE and CAE with BNFs instead of MFCCs. Best performance was achieved using the CAE trained with BNFs as input. This model combines the benefit of labelled data in well-resourced out-of-domain languages with a technique that can be used on extremely sparse in-domain data. Another interesting finding is that, in the absence of multilingual resources to train a BNF extractor, features from a CAE trained on MFCCs perform equally well. In future work we plan to integrate this model into our larger keyword spotting framework \cite{6}, and to apply it to languages such as Somali, Rutooro and Lugbara, which are spoken in areas where the system will next be deployed.
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