Spoken Term Detection Methods for Sparse Transcription in Very Low-resource Settings

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1. Introduction

Efforts are made across Australia to preserve, document and revitalize Aboriginal languages. These languages exist primarily in spoken form, and even if there is an official orthography it is not widely used by local people. Making recordings of speakers has been a widespread practice for documenting traditional knowledge. However, such recordings are often not transcribed, making them hard to access.

Manual transcription is time consuming and is often described as a bottleneck \cite{11}. While automatic speech recognition (ASR) has seen great improvement in recent years \cite{2,3}, it relies on a large amount of annotated data. Attempts to build ASR systems for low-resource languages end up with high word error rate or single-speaker models making them of limited use in indigenous contexts \cite{4,5,6,7}.

Such methods assume that everything should be transcribed. \cite{8} describes a sparse transcription model where we only transcribe the words we can confidently recognise, using word-spotting, while leaving the transcription of more difficult sections for later, perhaps when a speaker is available \cite{9}. Based on this model, we propose a workflow which combines spoken term detection and human-in-the-loop to support transcription in under-resourced settings \cite{9}. Here, we focus on the spoken term detection stage of the workflow, trying to seek a higher-level word units, we can never transcribe.

Automatic phone recognition has seen progress with minimal data \cite{5,10}. While \cite{8} argues that phonetic transcriptions do not stand in for the speech data and cannot be segmented to generate the required higher-level word units, we can nevertheless use phone transcriptions as a speech encoding, retaining our commitment to the sparse transcription model. In this paper we show how this can be done, and compare it with another spoken term detection method, namely dynamic time warping (DTW) \cite{11}. We consider both methods as applied to two very low-resource languages, Kunwinjku (gup) and Mboshi (mdw).

2. Background

Several sources of annotated data can be used to support transcription. Combining automatic processes and human intervention can be a way to iteratively fine-tune a speech recognition model with newly produced data, and enhance the manual transcription with automatically annotated data. \cite{8} proposes a method that combines word spotting with human-in-the-loop in an iterative process. \cite{9} explore this further, using DTW with basic speech representations to transcribe up to 42% of a lexicon in their speech collection. However, this method is not robust in the face of speaker variability. Research around speech features for spoken term detection has explored the use of bottleneck features, or the hidden representation of an AutoEncoder \cite{12,13}, although they make negligible difference in the context of the workflow \cite{9}. Others have exploited neural approaches to train word classifiers from words pair using Siamese loss \cite{14,15}, however pairs of words are required, limiting the selection of words that can be searched.

While standard automatic speech recognition methods tend to give poor performance in low-resource setting \cite{4,5}, recent work has shown that it is possible to obtain an automatic phone transcription with minimal training \cite{5,10,16}. In the context of word-level transcription, \cite{8} describes phone transcription as a ‘retrograde step’ given that optimising the recognition of low-level units such as phones does not necessarily help with identifying higher-level units. He also observes that only linguists can provide the required phone transcriptions or grapheto-phone rules. In many spoken languages, we can find standard orthographies and a small amount of spoken material transcribed. These orthographies are built in a written system close to the language phonology. Such system is documented enough so an approximate phone transcription can be easily obtained through a basic mapping from graphemes to phonemes on existing written data \cite{17}. Explain that the linguist should aim for a faithful phones transcription to aim to a better Phone Error Rate (PER). However a noisy phones transcription or even an orthographic transcription mapped into phonemes can also be used to train a phone recognizer. Phone transcription has this advantage over speech representation that its level of abstraction gives a speaker-independent representation.

Doing word spotting, while some terms are unlikely to be found in a noisy phone transcription, doing exact matching between the written forms of a lexicon (transliterated into phones) and a stream of the k-best phones output by the recogniser offers inter-speaker robustness.

In the context of textual data annotation, \cite{18} argues that an automatic annotation is likely to improve the speed of the annotator if the precision is at least 80% and the accuracy if

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it is at least 60%. Even though a wide set of factors can have an influence on the speed and accuracy, like the quality of the data or the confidence of the transcriber, we argue that a higher precision is to be prioritized over a higher recall.

3. Methods

We begin with a lexicon of size $s$ consisting of audio clips of spoken words, along with their orthographic transcription, and a speech collection in which more instances of those words may be found. Two spoken term detection approaches are investigated here: (a) a baseline method based on DTW applied on MFCC features (normalized for cepstral mean and variance); and (b) a method based on automatic phone recognition in which phones units are mapped to word units (P2W).

3.1. Baseline: Sparse Transcription using DTW

The baseline is a simplified version of the workflow of [9] which introduced an iterative process to transcribe speech with a growing spoken lexicon. We use DTW to retrieve lexical items from the speech collection, sliding query terms across the utterances. For each entry in the lexicon, based on the DTW score, we select the $n$ best matches in the collection to be evaluated. The value of $n$ has been optimized using a development set ($n = 5$ for Kunwinjku and $n = 20$ for Mboshi).

3.2. Sparse Transcription using Phone Recognition (P2W)

[10] introduced Allosaurus, a universal phone recognition system which combines a language independent encoder and phone predictor, and a language dependent allophone layer and a loss function associated with each language (Fig. 1). Allosaurus models are trained using standard phonetic transcriptions and the allovera database [19], a multilingual allophone database that can be used to map allophones to phonemes. The model first encodes speech with a standard ASR encoder which computes the universal phone distribution. Then an allophone layer is initialized with the allophone matrix and maps the universal phone distribution into the phoneme distribution for the given target language. The resulting model can be fine-tuned and applied to unseen languages.

In the current context, since we only have an orthographic transcription for Kunwinjku, we transliterate it into IPA (Fig. 2a) with the mapping shown in Table 1. The transcription contains some English words which will be mapped as if they were Kunwinjku words (e.g., school is written /sPko/ instead of /sko/). For Mboshi, the orthographic transcription already mostly matches the corresponding phonetic transcription.

We fine-tuned the original pretrained model with the training subsets described in Section 4 following the mapping described above resulting on one new phone recognition model per language (Fig. 2b). We used the resulting models to automatically transcribe the validation set of the two languages (Mboshi and Kunwinjku) (Fig. 2c). For Kunwinjku, we reverse the mapping function to get a grapheme transcription (Fig. 2d). Finally, we use the written lexicon for each language and perform spoken term detection using the queries’ transcripts using a longest string matching algorithm (Fig. 2e).

4. Data

The same datasets of [9] will be used: a corpus in Kunwinjku which consists of 301 utterances aligned with an orthographic transcription and a forced alignment created using the MAUS forced aligner [20], and a corpus in Mboshi which consists of 5130 utterances elicited from text, with orthographic transcription and a forced alignment at the word level [21].

In order to train the phone recognition system, an additional collection of 20 min of Kunwinjku (newly recorded guided tours) is used as training set. For Mboshi, a subset of 30 min is randomly extracted from the original corpus.

The lexicon queries (for spoken term detection) are made of 100 words for Mboshi and 60 words for Kunwinjku. We randomly selected words which occur at least 3 times. For each word, we manually selected examples clearly pronounced, verified and respecting the speaker distribution of the corpora (Table 2 and 3) and clipped them out of the corpora used for spoken term detection.

| Speaker | RB | TG | GN | SG | MM |
|---------|----|----|----|----|----|
| Distribution | 10% | 25% | 15% | 38% | 12% |

Table 2: Speaker distribution across Kunwinjku lexicon

1The tones are marked in the orthographic transcription but this feature is not taken into account in the Allosaurus model. We thus decided to treat the orthographic transcription as a phonetic transcription so the accentuated vowels are considered as new phones.
5. Results

We first evaluate the phone error rate (PER) for both languages. For Kunwinjku the PER started at 53.15%, and we obtained 40.55% after the system early stopped at the 17th epoch. For Mboshi the PER started at 59% and reached 35.49% at the 29th epoch. Although the PER is low considering the small amount of data used for fine-tuning Allosaurus, we would expect a bigger difference between Kunwinjku and Mboshi considering that Mboshi is read speech without foreign words and Kunwinjku is spontaneous speech containing English words.

We evaluate the two spoken term detection approaches presented in previous section, using recall and precision. Since the recall of the baseline includes the words from the lexicon used as queries, we also provide the recall without the instances of the lexicon (recall-no-lex). The F-score is computed using regular recall. In the case of Kunwinjku, the size of the validation set is small, which means that the words from the lexicon represent a large portion of the final results.

|      | recall-no-lex | recall | precision | F-score |
|------|---------------|--------|-----------|---------|
| DTW  | 17.43%        | 33.24% | 21.67%    | 26.24%  |
| P2W  | -             | 15.15% | 85.07%    | 25.72%  |

Table 4: Performance of spoken term detection in Kunwinjku

|      | recall-no-lex | recall | precision | F-score |
|------|---------------|--------|-----------|---------|
| DTW  | 15.47%        | 21.18% | 13.55%    | 16.53%  |
| P2W  | -             | 13.07% | 62.91%    | 21.64%  |

Table 5: Performance of spoken term detection in Mboshi

Results are detailed in Table 4 for Kunwinjku and in Table 5 for Mboshi. DTW has an advantage over P2W that it allows us to look deeply into the speech collection and so to retrieve more items and increase the recall, while decreasing precision.

P2W allows us to navigate into a limited number of symbols and matched words from an initial lexicon. This method allows us to navigate only in the stream of symbols automatically generated which makes the word matching results highly dependent of the phones recognition performance. However, navigating into written forms allows very accurate matches and a high precision since we are matching only exact same forms between the lexicon and the unsegmented stream of characters. The lower precision for Mboshi can be explained by the fact that this language has tones which increases the number of confusable vowels.

We mentioned in Section 2 that DTW and phone recognition have their own strength. DTW will cope easily with spontaneous speech and sounds elision due to co-articulation effects. Phone recognition allows us to avoid gathering spoken query and retrieve terms with exact matching between written forms. To highlight the complementary of the two methods, we analyse the intersection of their true positives in figure 5. We show that for both corpora the intersection of the true positives are small and combining the two methods can help us increase the coverage of the transcription.
Algorithm 1 search of the phoneme confusion network

```
token ← None
valid ← None
i ← 0
while i ≤ confnet[0].length do
  for each phone ∈ confnet[i] do
    if confnet[i][phone] ∈ lexState.current.validPath then
      token ← token + confnet[i][phone]
      lexState.current ← confnet[i][phone]
      if lexState.current.isword then valid ← token
    end if
    if savePoint = None then savePoint ← i
  end for
  else
    if valid ≠ None then return valid
    savePoint ← None
    if lexState.current ← lexState.root
      token ← None
      if valid ≠ None then return valid
    end if
  end if
  i ← i + 1
end while
```

The idea is to check in the confusion network (confnet) for each top k phone from the most likely to the least likely if it corresponds to a valid path in the lexicon (lexState). If a given phone is recognized as a final state in the lexicon, the corresponding word is kept as a candidate. If a followed path cannot find a final state, the search starts back from the index corresponding to the first state recognized. This is a basic search which allows us to easily explore the network but could be optimized following a Viterbi algorithm adapted for this task. An illustration of the search is shown in Figure 6 where we start searching for *manu*. The search starts back from a since no final state has been found. No phone is recognized as a valid state until *b*. The search ends recognizing *bun*.

Figure 6: search of the phoneme confusion network with lexicon stored in a trie

We applied this search on the top 5 phonemes applying a pruning of the network based on two arbitrary thresholds (0.2 and 0.1). We then compute the same evaluation described in Section 6 and report the results in Tables 6 and 7.

We can see that a simple search allows us to boost the recall maintaining the precision at an acceptable rate. We can also see that P2W with a pruning set at 0.2 outperforms the DTW baseline in terms of recall when the spoken lexicon is not included in the results.

7. Conclusion

Although traditional methods of spoken term detection are more robust in spontaneous speech and cope more easily with speech elision due to coarticulation effects, the phone recognition based approach appears to be much more accurate mostly because of its speaker independence. Even if cleaner data is to be privileged for fine-tuning the model for better recall, a noisy transcription can still be usable. In the context of interactive transcription, precision is to be privileged over recall in order to properly assist the transcriber limiting the correction of wrong output.

The spoken lexicon required by DTW can be hard to collect: we saw that differences of speaker between the corpus and the lexicon have a impact on the final precision which force us to carefully select the example to be used and extract them manually. A phone recognition based approach would only need a written lexicon.

Phoneme recognition based methods give us the possibility of quickly and precisely exploring the content of a given speech collection through simple textual queries. The confusion network output by Allosaurus lets us enable a deeper search, replacing a given phone by another. Such exploration outperforms the DTW baseline in terms of recall, while maintaining high precision.

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9. References

[1] C. Brinckmann, “Transcription bottleneck of speech corpus exploitation,” Proceedings of the 2nd Colloquium on Lesser Used Languages and Computer Applications, pp. 165 – 179, 2009.

[2] D. Povey, A. Ghoshal, G. Boulianne, L. Burget, O. Glembek, N. Goel, M. Hannemann, P. Motlicek, Y. Qian, P. Schwarz, J. Silovsky, G. Stemmer, and K. Vesely, “The kaldi speech recognition toolkit,” in IEEE 2011 Workshop on Automatic Speech Recognition and Understanding, IEEE Signal Processing Society, Dec. 2011, iEEE Catalog No.: CFP11SRW-USB.

[3] S. Watanabe, T. Horii, S. Karita, T. Hayashi, J. Nishitoba, Y. Unno, N. E. Y. Soplin, I. Heymann, M. Weisner, N. Chen et al., “Espnet: End-to-end speech processing toolkit,” Proc. Interspeech 2018, pp. 2207–2211, 2018.

[4] V. Gupta and G. Boulianne, “Automatic transcription challenges for Inuktitut, a low-resource polysynthetic language,” in Proceedings of the 12th Language Resources and Evaluation Conference, 2020, pp. 2521–27.

[5] ——, “Speech transcription challenges for resource constrained indigenous language Cree,” in Proceedings of the 1st Joint Workshop on Spoken Language Technologies for Under-Resourced Languages and Collaboration and Computing for Under-Resourced Languages (CCURL), 2020, pp. 362–367.

[6] B. Foley, J. T. Arnold, R. Coto-Solano, G. Durantin, T. M. Ellison, D. van Esch, S. Heath, F. Kratochvil, Z. Maxwell-Smith, D. Nash et al., “Building speech recognition systems for language documentation: The coedl endangered language pipeline and inference system (elpis).” in SLTU, 2018, pp. 205–209.

[7] O. Adams, B. Galliot, G. Wisniewski, N. Lambourne, B. Foley, R. Sanders-Dwyer, J. Wiles, A. Michaud, S. Guillaume, L. Besacier et al., "User-friendly automatic transcription of low-resource languages: Plugging espnet into elpis," in ComputEL-4: Fourth Workshop on the Use of Computational Methods in the Study of Endangered Languages, 2020.

[8] S. Bird, “Sparse transcription,” Computational Linguistics, vol. 46, pp. 713–744, 2020.

[9] E. Le Ferrand, S. Bird, and L. Besacier, “Enabling interactive transcription in an indigenous community,” in COLING 2020, 2020.

[10] X. Li, S. Dalmia, J. Li, M. Lee, P. Littell, J. Yao, A. Anastasopoulos, D. R. Mortensen, G. Neubig, A. W. Black et al., “Universal phone recognition with a multilingual allophone system,” in ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2020, pp. 8249–8253.

[11] H. Sakoe and S. Chiba, “Dynamic programming algorithm optimization for spoken word recognition,” IEEE Transactions on Acoustics, Speech, and Signal Processing, vol. 26, pp. 43–49, 1978.

[12] R. Menon, H. Kamper, E. van der Westhuizen, J. Quina, and T. Niesler, “Feature exploration for almost zero-resource ASR-free keyword spotting using a multilingual bottleneck extractor and correspondence autoencoders,” Proceedings of Interspeech 2019, pp. 3475–3479, 2019.

[13] H. Kamper, M. Elsner, A. Jansen, and S. Goldwater, “Unsupervised neural network based feature extraction using weak top-down constraints,” in 2015 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2015, pp. 5818–22.

[14] S. Settle and K. Livescu, “Discriminative acoustic word embeddings: Recurrent neural network-based approaches,” in 2016 IEEE Spoken Language Technology Workshop (SLT). IEEE, 2016, pp. 503–510.

[15] S. Settle, K. Levin, H. Kamper, and K. Livescu, “Query-by-example search with discriminative neural acoustic word embeddings,” Proc. Interspeech 2017, pp. 2874–2878, 2017.

[16] O. Adams, T. Cohn, G. Neubig, H. Cruz, S. Bird, and A. Michaud, “Evaluating phonemic transcription of low-resource tonal languages for language documentation,” in LREC 2018 (Language Resources and Evaluation Conference), 2018, pp. 3356–3365.

[17] A. Michaud, O. Adams, T. A. Cohn, G. Neubig, and S. Guillaume, “Integrating automatic transcription into the language documentation workflow: Experiments with na data and the persephone toolkit,” 2018.

[18] P. L. Felt, “Improving the effectiveness of machine-assisted annotation,” Ph.D. dissertation, Brigham Young University-Provo, 2012.

[19] D. Mortensen, X. Li, P. Littell, A. Michaud, S. Rijhwani, A. Anastasopoulos, A. Black, F. Metze, and G. Neubig, “Allovera: a multilingual allophone database,” in LREC 2020: 12th Language Resources and Evaluation Conference, 2020.

[20] T. Kisler, U. Reichel, and F. Schiel, “Multilingual processing of speech via web services,” Computer Speech and Language, vol. 45, pp. 326–347, 2017.

[21] P. Godard, G. Adda, M. Adda-Decker, J. Benjumea, L. Besacier, J. Cooper-Leavitt, G.-N. Kouarata, L. Lamel, H. Maynard, M. Müller et al., “A very low resource language speech corpus for computational language documentation experiments,” arXiv preprint arXiv:1710.03501, 2017.

[22] L. Mangu, E. Brill, and A. Stolcke, “Finding consensus in speech recognition: word error minimization and other applications of confusion networks,” Computer Speech & Language, vol. 14, no. 4, pp. 373–400, 2000. [Online]. Available: https://doi.org/10.1006/csla.2000.0132.