Convolutional Speech Recognition with Pitch and Voice Quality Features

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Abstract

The effects of adding pitch and voice quality features such as jitter and shimmer to a state-of-the-art CNN model for Automatic Speech Recognition are studied in this work. Pitch features have been previously used for improving classical HMM and DNN baselines, while jitter and shimmer parameters have proven to be useful for tasks like speaker or emotion recognition. Up to our knowledge, this is the first work combining such pitch and voice quality features with modern convolutional architectures, showing improvements up to 2% absolute WER points, for the publicly available Spanish Common Voice dataset. Particularly, our work combines these features with mel-frequency spectral coefficients (MFSCs) to train a convolutional architecture with Gated Linear Units (Conv GLUs). Such models have shown to yield small word error rates, while being very suitable for parallel processing for online streaming recognition use cases. We have added pitch and voice quality functionality to Facebook’s wav2letter speech recognition framework, and we provide with such code and recipes to the community, to carry on with further experiments. Besides, to the best of our knowledge, our Spanish Common Voice recipe is the first public Spanish recipe for wav2letter.

Index Terms: automatic speech recognition, convolutional neural networks, pitch, jitter, shimmer

1. Introduction

Neural network models applied to automatic speech recognition (ASR) task are consistently achieving state-of-the-art results in the field. Some of the best scoring architectures involve transformer-based acoustic models [1], LAS models [2] with SpecAugment data augmentation [3] or models strongly based on convolutional neural networks, like the ResNets and TDS ones in [3].

Such convolutional approaches have the advantage of being able to look at larger context windows, without the risk of vanishing gradients like in pure LSTM approaches, and being suitable for online streaming applications, while attaining low word error rate (WER) scores. Furthermore, following the trend of making systems as end-to-end as possible, even fully convolutional neural approaches have been proposed, and shown state-of-the-art performances [3]. This fully convolutional architecture takes profit of stacking convolutional layers for efficient parallelization with gated linear units that prevent the gradients from vanishing as architectures go deeper [6].

Recently, Facebook has outsourced wav2letter [7], a very fast speech recognition framework with recipes prepared for training and decoding with some of these modern models, with an emphasis on the convolutional ones. Most of the modern architectures work only on cepstral (MFCCs) and mel-frequency spectral coefficients (MFSCs) inputs, or even directly with the raw waveform, and tending towards the increasing of granularity at input level by usually augmenting the number of spectral parameters. Whilst it seems evident whether current end-to-end deep network architectures are able to automatically perform relevant feature extraction for speech tasks, psychical or functional properties, related to the underlying speech production system, become fuzzy or difficult to connect with the speech recognition performances. In addition, it is still unclear how the great quantity and different speech hand-crafted voice features, carefully developed along past years and based on our linguistic knowledge, might help and in which degree to the current speech network architectures.

Some well-known speech recognition frameworks, like Kaldi [8], have incorporated the use of additional prosodic features, such as the pitch or the probability of voicing. These are stacked into an input vector together with those cepstral/spectral ones, and then forwarded to classifiers like HMM or DNN ensembles. Nevertheless, the newest convolutional architectures have not yet extensively applied along with such prosodic features, and frameworks like wav2letter, reaching state-of-the-art performances in ASR tasks, do not yet provide with integrated pitch functionality within feature extraction modules.

In the last decades, jitter and shimmer have shown to be useful in a wide range of applications; e.g. detection of different speaking styles [9], age and gender classification [10], emotion detection [11], speaker recognition [12], speaker diarization [13], and Alzheimer’s and Parkinson Diseases detection [14,15], among others.

The main contribution of this work is to perform a preliminary study on the effects of adding pitch and voice quality features, like jitter and shimmer, to the classical spectral coefficients employed in many state-of-the-art convolutional models. In order to do so, several combinations of such proposed features are assessed by simply appending them to the MFSCs for further analysis through following convolutional layers. We choose to carry all the experiments out with the Conv GLU model from wav2letter’s WSJ recipe [16], which have shown state-of-the-art performance for Librispeech and WSJ datasets. Finally, it is worth to mention that, to the best of our knowledge, this is the first attempt to use jitter and shimmer features within a modern deep neural-based speech recognition system while keeping easy to identify psychical/functional properties of the voice and link them to the ASR performance.

Furthermore, we have released our recipe adapted for wav2letter. It makes use of a public and freely available Spanish speech corpus, the Spanish Common Voice dataset [17]. Previous ASR recipe and the C++ code for extracting prosodic and voice quality features, within the wav2letter’s framework, can be found at a Github1 repository.

1https://github.com/gcambara/wav2letter
2. Voice features

Pitch and probability-of-voicing (POV) features have proved to increase performance in ASR systems, specially for tonal languages like Punjabi [18], but also with non-tonal languages like English [19]. There are various pitch extractor algorithms such as Yin [20] or getF0 [21], but we have decided to make a portion of Kaldi’s one [22], to wav2letter, since it has been frequently used and well tested during the recent years for ASR tasks. Such algorithm is based on getF0, and finds the sequence of lags that maximizes the Normalized Cross Correlation Function (NCCF).

Jitter and shimmer represent the cycle-to-cycle variations of fundamental frequency and amplitude, respectively. For a long time, they were relevant features to detect voice pathologies [23] [24], and thus considered as measurements of voice quality.

Although voice quality features differ intrinsically from those suprasegmental prosodic features, they have shown to be related to prosody. In [25], the authors showed that voice quality features are relevant markers signaling paralinguistic information, and that they should even be considered as prosodic parameters along with pitch and duration, for instance. It has been demonstrated that prosodic information can increase the performance of automatic speech recognition systems, like in [26], where the authors built an ASR for dysarthric speech, or [27], where the authors applied jitter and shimmer for noisy speech recognition, both of them using HMM models. Also, a neural network approach with LSTM was taken by [28], for acoustic emotion recognition task, however they did not perform ASR task on its own.

Thus and having previous evidences, we hypothesize that prosodic and voice quality features may boost robustness in ASR, and could play an even more important role in further speech tasks, including punctuation marks, emotion recognition or musical contexts, where additional prosodic information would be useful.

3. Methodology

3.1. Data

The effect of adding pitch and voice quality features is evaluated by means of the Common Voice corpus in Spanish [17]. This open-source dataset has been originally designed for speech synthesis purposes and consists of recordings from volunteer contributors pronouncing scripted sentences, recorded at 48kHz rate and using own devices. The sentences come from original contributor donations and public domain movie scripts and it is continuously growing. Although there are already more than 100 hours of validated audio, we have kept a reduced partition of approximately 19.0 h for training, 2.7 h for development and 2.2 h for testing sets. The main criterion for the stratification of such partitions is to ensure that each one has exclusive speakers, while trying to keep a 80-10-10% proportion. Every sample can be down voted by the contributors if it is not clear enough, so we have discarded all samples containing at least one down vote, to keep the cheery picked recordings as clean as possible. Afterwards, we try to keep as balanced as possible the distributions by age, gender and accent. The Python scripts for obtaining such partition are provided in our public Git repository, along with other code necessary to reproduce our ASR recipes. Up to our knowledge, this is the first public repository with a wav2letter recipe for a publicly available Spanish dataset.

3.2. Feature Extraction

As recommended by wav2letter’s Conv GLU recipes, raw audio is processed to extract static Mel Frequency Spectral Coefficients (MFSCs), applying 40 filterbanks. This serves as our baseline, so on top of it we append pitch and voice quality related features. From now on in this work, when we talk about pitch features we refer to the following three features: the extracted pitch itself, plus the probability-of-voicing (POV) for each frame and the variation of pitch across two frames (delta-pitch). Being so, 40 MFSCs are always computed for each time frame, and if specified by the user in the configuration, the three pitch features (pitch, POV and delta-pitch) can be appended to them, plus jitter relative, jitter absolute, shimmer dB and/or shimmer relative.

The pitch extraction algorithm is a simpler version of the one implemented in Kaldi [22], which uses the classic Viterbi algorithm for obtaining the optimal lags, and applies the logarithm to the pitch values as the only post-processing step. This way the pitch values are compressed to the same order as the MFSCs, which are compressed by the logarithm as well, ensuring numerical stability later on during the training phase. Subtracting the weighted average pitch during post-processing has been discarded, since the reported gains in WER by Kaldi are only of a 0.1%, but we may implement them in future iterations.

Shimmer is computed measuring the peak-to-peak waveform amplitude at each period where the pitch is extracted, and then performing the corresponding operations, depending on whether we deal with shimmer dB or shimmer relative, see reference [12]. With the pitch extracted at each period, the same can be done for jitter absolute and relative, by calculating the fundamental frequency differences between such cycles.

3.3. System Architecture

Since our purpose is to study how pitch and voice quality features contribute to a convolutional acoustic model (AM), we have used the Conv GLU AM from wav2letter’s Wall Street Journal (WSJ) recipe [16]. This model has approximately 17M parameters with dropout applied after each of its 17 layers. The WSJ dataset contains around 80 hours of audio recordings, which is closer to the magnitude of our data than the LibriSpeech recipe (about 1000 hours). We have not done an extensive exploration of architecture parameters, since it yields decent out of the box results with Common Voice data, enough to perform the comparisons proposed for this work.

Regarding the lexicon, we use a grapheme-based one extracted from the approximately 9000 words from both the training and development partitions. We use the standard Spanish alphabet as tokens, plus the “” letter from Catalan and the vowels with diacritical marks, making a total of 37 tokens. The “” character is included because of the presence of some Catalan words in the dataset, like “Bara”. The language model (LM) is a 4-gram model extracted with KenLM [29] from the training set. Since most of the sentences are shared across partitions, due to the scripted nature of the dataset, we expected an optimistic behavior after applying such LM. Therefore, we are also reporting results given by another 4-gram LM extracted from the Spanish Fisher+Califome. The Fisher corpus splitting is taken from the Kaldi’s recipe [30]. Decoding across AM, lexicon and LM is done with the beam-search decoder provided by wav2letter [31]. Furthermore, in order to assess the capacity of the AM by itself, we also evaluate without LM, choosing the final characters with the greedy best path from the predictions of the AM.
The learning rate is tweaked to 7. The Segmentation Criterion (ASG) [16], inspired by CTC loss [32]. The inferred segmentation is taken out from wav2letter’s Auto experiment are the same, all based on wav2letter’s WSJ recipe.

LDC Spanish corpus of the Fisher-Callhome (FCLM).

A 4-gram LM trained with the Common Voice’s training subset (CVLM) and a 4-gram LM obtained with the training partition from the LDC Spanish corpus of the Fisher-Callhome (FCLM).

| Features                  | AM WER (%) |
|---------------------------|------------|
| MFSC                      | 64.92      |
| MFSC+Pitch                | 63.18      |
| MFSC+Pitch+Jitter         | 63.83      |
| MFSC+Pitch+Shimmer        | 73.18      |
| MFSC+Pitch+Shimmer+Jitter | 64.46      |

| Features                  | WER (%)   |
|---------------------------|-----------|
| NoLM-Dev                  | 64.92     |
| NoLM-Test                 | 70.07     |
| CVLM-Dev                  | 20.29     |
| CVLM-Test                 | 24.72     |
| FCLM-Dev                  | 38.58     |
| FCLM-Test                 | 44.20     |

3.4. Experiments

After some initial testing, we have found that the most stable voice quality features are jitter relative and shimmer relative, so we try 5 different feature configurations: 40 MFSCs only, 40 MFSCs + 3 pitch features, 40 MFSCs + 3 pitch features + 1 jitter relative feature, 40 MFSCs + 3 pitch features + shimmer relative feature and 40 MFSCs + 3 pitch features + 1 jitter relative feature + 1 shimmer relative feature. These are the 5 experiments ran in this work, and for each one of them, WERs are evaluated with Common Voice’s dev and test sets. Decodings are done without LM (NoLM), with Common Voice’s LM (CVLM) and Fisher+Callhome’s LM (FCLM). Therefore, we obtain 6 WERs for each one of the 5 feature configurations.

Besides the features, the training configurations for each experiment are the same, all based on wav2letter’s WSJ recipe. The inferred segmentation is taken out from wav2letter’s Auto Segmentation Criterion (ASG) [16], inspired by CTC loss [32]. The learning rate is tweaked to 7.3, and is decayed in a 20% every 10 epochs. A 25 ms rolling window with a 10 ms stride is used for extracting all the features, jitter and shimmer are averaged across 500 ms windows.

For beam-search decoding, the following settings are used: LM weight set to 2.5, word score set to 1, beam size set to 2500, beam threshold set to 25 and silence weight set to -0.4. In order to tune these, we have not run an extensive exploration of hyperparameters, but after a shallow search we found these to provide good results for both LMs.

4. Results and Discussion

Table 1 reports the WER (%) error rates for each one of the 5 feature configurations, for the proposed decodings of Common Voice’s dev and test sets, without LM (NoLM), with its own LM (CVLM) and the Fisher+Callhome LM (FCLM). For every evaluated case, the best WER score is always provided by one of the models using pitch features, or pitch with voice quality (jitter + shimmer) features, with gains between 0.28% and 1.82% absolute WER points.

For the cases without LM, the model with MFSC and pitch features is the one with the best performance, with gains of 1.74% and 1.28% for dev and test sets, respectively. Additional features on the other models also improve the WER score, except for the case with pitch and shimmer only, which yields worse results across all experiments.

On the other hand, decoding with CVLM achieves the best WER scores, when training with all the proposed features together: MFSCs, the 3 pitch features, jitter relative and shimmer relative. A 20.01% WER is obtained for the dev set, and a 22.90% WER for the test set. As it was expected, the CVLM improves drastically the predictions, because even though it is obtained from the train partition solely, many sentences are shared with the dev and test sets, due to the reduced vocabulary in this dataset.

A more realistic approach is to decode by using an external LM. The FCLM language model is built from the training partition of the LDC Spanish Fisher+Callhome corpus. Although the LM enrollment is performed with less than 20 hours of audio (approximately 16k sentences), it still yields to a reasonable performance compared to the CVLMs decodings. With respect to the prosodic features, the FCLM beam decoding reaches the lower WER rates in development by using MFSCs only augmented with pitch features, that is, 37.57% WER. The lowest 42.95% WER score in the test set is given by the combination of all pitch and voice quality characteristics. Once again, the best results in terms of WER are provided by models with pitch features, or pitch features with the combination of jitter and shimmer, showing the potential of pitch and voice quality features to improve the performance of an ASR based on convolutional neural networks.

Nonetheless, it is worth to notice how the use of only pitch and shimmer features yields to worse performance for both AM and AM/LM decoding models. Previous behaviour is depicted in the Figure 1, where using only shimmer dramatically affects the training stage of the model, making it worse and slower. However, training with pitch features or with pitch and jitter features seems to help at reaching better WER plateaus and at faster pace.

While jitter is a measure of frequency instability in the wave, shimmer is a measure of amplitude instability. Being so, pitch and jitter characteristics might contribute to MFSCs spectral features with independent information, just by synchronising them in a simple concatenation like the proposed one. However, the inclusion of shimmer, which is related to amplitude, as opposed to the others, related to frequency, is more likely to be understood as a perturbation throughout the convolutional layers that might difficult the acoustic model training.
5. Conclusions

This study performs a preliminary exploration on the effects of pitch and voice quality measurements (jitter and shimmer) within the framework of the ASR task performed by convolutional neural network models. The experiments reported with a publicly available Spanish speech corpus showed consistent improvements on the model robustness, achieving almost a reduced absolute 2% WER in some scenarios. Besides, such feature extraction functionalities are provided and integrated with.wav2letter code for easily replicate our findings or directly apply pitch and voice quality features to.wav2letter models. We also provide the recipe for the Common Voice Spanish dataset, the first recipe suited for.wav2letter using a Spanish publicly available dataset. Further steps on the research of convolutional ASR with pitch and voice quality would imply adapting architectures for feature processing, or applying such characteristics for tasks including the presence of punctuation marks, emotion recognition and even pathological or singing voices. For the latter tasks, the importance of pitch and voice quality features is expected to become more relevant.

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Figure 1: Common Voice dev set WER(%) error rates during training, as a function of the epoch number, curves across the 5 different feature configurations for the same acoustic model architecture.

Even though, it is interesting to see how if shimmer is coupled with jitter and pitch characteristics altogether, the performance obtained yields to more robust results compared to the baseline and independently of decoding with CVLM and FCLM language models. Other studies already suggest the correlation between jitter and shimmer by the same index, that is, the Voice Handicap Index (VHI) [33], so the convolutional filters may be finding similar correlations, thus improving mutual information when coupled together with spectral features and promoting such as voice measurements as good feature candidates for enhancing the speech recognition of pathological voices. The latter being an interesting hypothesis to look for further evidence.

Appending pitch characteristics (pitch itself, probability-of-voicing and delta-pitch) to MFSC features seems to slightly improve performance across all the experiments, being MFSC+pitch and MFSC+pitch+jitter+shimmer the combinations that provide the most robust behavior. These carry prosodic information that helps boosting the accuracy of the convolutional neural network acoustic model with gated linear units used here, a state-of-the-art architecture suitable for data parallelization and robust behaviour against vanishing gradients. For the evaluated Spanish Common Voice dataset, this effect is specially noticeable when decoding without LM or with an external LM such as the FCLM, because of the limited vocabulary giving a stronger weight to the CVLM.

The approach for this preliminary exploration on such configurations has been simple, by just appending such features to the spectral ones, without extensive post-processing of these nor adaptations of the model architecture. Being so, it is reasonable to think that there is still margin of improvement in the application of pitch and voice quality measurements to state-of-the-art convolutional neural models. Possible strategies comprises adapting the feature concatenation, maybe by dedicating exclusive filters to the new pitch and voice quality features, especially after experimentally realising, not reported in this work, that the estimation of measurements like shimmer may benefit from different post-processing techniques.
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