Applying Speech Tempo-Derived Features, BoA W and Fisher Vectors to Detect Elderly Emotion and Speech in Surgical Masks

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Abstract

The 2020 INTERSPEECH Computational Paralinguistics Challenge (ComParE) consists of three Sub-Challenges, where the tasks are to identify the level of arousal and valence of elderly speakers, determine whether the actual speaker wearing a surgical mask, and estimate the actual breathing of the speaker. In our contribution to the Challenge, we focus on the Elderly Emotion and the Mask sub-challenges. Besides utilizing standard or close-to-standard features such as ComParE functionals, Bag-of-Audio-Words and Fisher vectors, we exploit that emotion is related to the velocity of speech (i.e. speech rate). To utilize this, we perform phone-level recognition using an ASR system, and extract features from the output such as articulation tempo, speech tempo, and various attributes measuring the amount of pauses. We also hypothesize that wearing a surgical mask makes the speaker feel uneasy, leading to a slower speech rate and more hesitations; hence, we experiment with the same features in the Mask sub-challenge as well. Although this theory was not justified by the experimental results on the Mask Sub-Challenge, in the Elderly Emotion Sub-Challenge we got significantly improved arousal and valence values with this feature type both on the development set and in cross-validation.

Index Terms: speech recognition, human-computer interaction, computational paralinguistics

1. Introduction

Computational paralinguistics, a subfield of speech technology, deals with extracting, locating and identifying various phenomena being present in human speech. In contrast with Automatic Speech Recognition (ASR), where most of such information is considered secondary behind the phonetic content of the speech signal (i.e. the phonetic or word-level transcription), computational paralinguistics focuses on the huge variety of information related to the physical and mental state of the speaker, usually ignoring the actual words uttered. The Interspeech Computational Paralinguistics Challenge (ComParE), held regularly at the Interspeech conference over a decade now, focuses on the automatic identification of this ‘paralinguistic’ (that is, ‘beyond linguistic’) aspect of human speech. The open tasks presented over the years covered dozens of different human speech aspects, ranging from emotion detection [1] through determining speaker age and gender [2], estimating blood alcohol level [3] and identifying specific disorders which affect the speech of the subject (e.g. autism [4] and Parkinson’s Disease [5]).

During the history of the ComParE Challenge, we can see two main types of solutions for the various tasks. The first employs general techniques, that might be applied for a wide range of problems. Perhaps the most straightforward such technique is the 6373-sized ‘ComParE functionals’ attribute set, which uses means, standard deviations, percentile statistics (e.g. 1st, 99th), peak detection etc. to form utterance-level attributes from certain frame-level feature vectors. This feature set was also developed over the years, taking its final form in 2013 (for the details, see the work of Schuller et al. [4]). Another such approach is the Bag-of-Audio-Words (or BoA W, [6,7,8]) method, which first clusters the input frame-level feature vectors, and then assigns each frame of each utterance into one of these clusters and uses a statistics of these clusters to construct an utterance-level feature vector. This technique is incorporated into the Challenge baselines since 2017 [9]. Some other feature extraction methods, albeit being of a general nature, were only employed by certain participants so far, such as Fisher vectors [10,11,12].

The second type of approaches seek to employ task-specific techniques. Clearly, one might expect that a solution designed and fine-tuned for the actual problem at hand allows higher performance, leading to better accuracy scores; on the other hand, they take more effort to develop. For example, Grézes et al. calculated the ratio of speaker overlap to aid conflict intensity estimation [13]; Montacié and Caraty detected temporal events (e.g. speech onset latency, event starting time-codes, pause and phone segments) to detect cognitive load [14]. Several authors extracted phone posterior-based attributes to determine the degree of nativeness or the native language of the speaker [15,16,17], while Huckvale and Beke developed specific spectral-based attributes to detect whether the speaker has a cold [18]. Of course, some kind of fusion of the general and the task-specific attributes might also prove to be beneficial.

In our actual contribution to the ComParE 2020 Challenge [19], we apply specific task-dependent attributes. It is well-known that the mental state of the subject affects several prosodic and temporal properties of his speech, specifically, emotion is strongly related to speech tempo [20,21], and it affects the amount of hesitation as well. This means that, by our hypothesis, calculating temporal parameters such as articulation tempo (i.e. phones uttered per second), speech tempo and some pause-related attributes, we might be able to estimate the emotional state of the speaker. In other paralinguistic tasks, these attributes might be indicators of different speaker states, e.g. feeling uneasy when forced to speak in a surgical mask. Of course, competitive performance is probably achieved via a combination of predictions with those obtained by using standard approaches, such as ComParE functionals or Bag-of-Audio-Words (BoAW).

Following the Challenge guidelines (see [19]), we will omit the description of the tasks, datasets and the method of evaluation, and focus on the techniques we applied. Since the Breathing sub-challenge is essentially a frame-level (or a few-frame-level) task, which calls for entirely different techniques, we focus on the remaining two sub-challenges in this study: in the
that the speaker was recorded while wearing a surgical mask or not, while in the Elderly Emotion Sub-Challenge (ESC) the task is to determine the affective state of subjects aged 60 or over. While the former is a binary classification task, in the Elderly Emotion Sub-Challenge both arousal and valence have to be classified as low, medium or high, therefore it essentially consists of two three-class classification tasks. Classification performance is measured via the Unweighted Average Recall (UAR) metric; for the Elderly Emotion task, the UAR values corresponding to arousal and valence are averaged out.

2. Temporal Speech Features

Next we describe the temporal speech features we extracted from the utterances of the Elderly Emotion and Mask Sub-Challenges. We would like to note that this attribute set was based on our previous works focusing on detecting Mild Cognitive Impairment (MCI), Alzheimer’s Disease (AD) and schizophrenia (SCH) (see e.g. [22, 23, 24]), with some straightforward changes. That is, we removed the calculation of the utterance length, as it was meaningless for the short speech chunks provided for the particular sub-challenges. For the list of our temporal parameters, see Table 1.

These speech parameters rely on the concept of hesitations. The simpler form of pause or hesitation is that of a silent pause: the absence of speech. However, filled pauses (sounds like “er”, “um” etc.) also indicate hesitations, and can take up a significant amount of speech time. For example, Tóth et al. found that about 10% of the hesitations in a Hungarian speech database appear as filled pauses [25]. While the simplest of our attribute, speech tempo corresponds to the average number of phones found in one second of the utterance, in articulation rate we take into account only those phones which are, in fact, are not hesitations. The remaining attributes (i.e. (3)-(6)) all describe the amount of hesitation within speech, but in different ways. Furthermore, when we describe the amount of pauses, we can take into account only silent pauses, only filled pauses, or any of them; so the temporal parameters (3)-(6) can be calculated in three variations, leading to a 14-sized attribute set.

To calculate these temporal parameters, first we performed speech recognition; as we were interested in these specific parameters, we decided to work only on the level of phones. While completely discarding a word-level language model (even as simple as a vocabulary) probably increases the number of errors in the ASR output, notice that now we do not need to be able to accurately identify the phones: all we need to do is to count them. We need to identify only two phenomena: silences (including breath intakes and sighs) and filled pauses. In this approach, we treated filled pauses as a special ‘phoneme’ from our previous experience, we also expected that silent and filled pauses can be identified with a high accuracy.

Although the speech material of both the Elderly Emotion and the Mask Sub-Challenges contained German speech, due to the absence of a German speech corpus we trained our DNN acoustic models on Hungarian speech samples. We were able to exploit this since both silent and filled pauses appear to be quite language-independent and because these two languages are quite similar on the phonetic level. We used a roughly 44 hours subset of the BEA corpus [27], where the annotation included several non-verbal acoustic cues such as breath intakes, sighs, coughs, and most importantly, filled pauses. We used our custom DNN implementation [28], and a modified version of HTK [29] for decoding, using a (Hungarian) phone bi-gram as a language model.

3. General Feature Extraction Methods

Next, we briefly describe the three standard feature extraction approaches we utilized in the ComParE 2020 Challenge.

3.1. ‘ComParE functionals’ Feature Set

Firstly, we used the 6373 ComParE functionals (see e.g. [4]), extracted by using the openSMILE tool [31]. The feature set includes energy, spectral, cepstral (MFCC) and voicing related frame-level attributes, from which specific functionals (like the mean, standard deviation, percentiles and peak statistics) are computed to provide utterance-level feature values.

3.2. Bag-of-Audio-Words Representation

The BoA approach also seeks to extract a fixed-length feature vector of a varying-length utterance [6]. Its input is a set of frame-level feature vectors such as MFCCs. In the first step, clustering is performed on these vectors, the number of clusters (N) being a parameter of the method. The list of the resulting cluster centroids will form the codebook. Next, each original feature vector is replaced by a single index representing the nearest entry in the codebook (vector quantization). Then the feature vector for the given utterance is calculated by generating a histogram of these indices, usually after some kind of normalization (e.g. in L1 normalization we divide each cluster count by the number of frames in the given utterance).

To calculate the BoA representations, we utilized the OpenXBOW package [2]. We tested codebook sizes of N = 32, 64, 128, 256, 512, 1024, 2048, 4096, 8192 and 16384. We employed random sampling instead of kmeans++ clustering for codebook generation [5], and employed 5 parallel cluster assignments; otherwise, our setup followed the ComParE 2020 baseline paper (i.e. [31]): we used the 65 ComParE frame-level attributes as the input after standardization, and a separate codebook was built for the first-order derivatives.

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Table 1: The examined temporal speech parameters, based on the work of Hoffmann et al. [30] and Tóth et al. [22].

| Parameter                          | Formula                                                                 |
|------------------------------------|-------------------------------------------------------------------------|
| Speech tempo                       | the number of phones per second (including hesitations).                |
| Articulation rate                  | the number of phones per second during speech (excluding hesitations).  |
| Pause occurrence rate              | divide the total number of pauses by the number of phonemes in the utterance. |
| Pause duration rate                | divide the total duration of pauses by the length of the utterance.     |
| Pause frequency                    | divide the number of pause occurrences by the length of the utterance.  |
| Average pause duration             | divide the total duration of pauses by the number of pauses.            |

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1Yes, the quotes are there for a reason, Mr. Moore [26].
3.3. Fisher Vector Representation

The aim of the Fisher vector representation is to combine the generative and discriminative machine learning approaches by deriving a kernel from a generative model of the data \[F_{\theta}\]. First we describe the original version, developed for image representation; then we turn to the application of Fisher vectors to audio.

The main concept of the Fisher Vector (FV) representation, adapted to audio processing, is to take the frame-level feature vectors of some corpus and model their distribution by a probability density function \(p(X|\Theta)\), \(\Theta\) being the parameter vector of the model. For example, when using Gaussian Mixture Models with a diagonal covariance matrix, \(\Theta\) will correspond to the priors, and the mean and standard deviation vectors of the components. The Fisher score describes \(X\) by the gradient \(G_{\Theta}X\) of the log-likelihood function, i.e.

\[
G_{\Theta}X = \frac{1}{T} \nabla_{\Theta} \log p(X|\Theta).
\]

This gradient function describes the direction in which the model parameters (i.e. \(\Theta\)) should be modified to best fit the data. The Fisher kernel between the frame-level feature vector sequences (i.e. utterances) \(X\) and \(Y\) is then defined as

\[
k(X, Y) = G_{\Theta}X^{T}F_{\Theta}^{-1}G_{\Theta}Y,
\]

where \(F_{\Theta}\) is the Fisher information matrix of \(p(X|\Theta)\), defined as

\[
F_{\Theta} = E_X[\nabla_{\Theta} \log p(X|\Theta)]\nabla_{\Theta} \log p(X|\Theta)^T.
\]

Expressing \(F_{\Theta}^{-1}\) as \(F_{\Theta}^{-1} = L_{\Theta}^{-1}L_{\Theta}^T\), we get the Fisher vectors as

\[
G_{\Theta}X = L_{\Theta}G_{\Theta}X = L_{\Theta}\nabla_{\Theta} \log p(X|\Theta).
\]

We used the open-source VLFeat library \[34\] to fit GMMs and to extract the FV representation; we fitted Gaussian Mixture Models with \(N = 2, 4, 8, 16, 32, 64\) and 128 components. As the input frame-level feature vectors, we here again employed the 65 ComParE frame-level attributes; following our previous experiments (e.g. \[11\] \[25\]), we also employed the first-order derivatives (i.e. the \(\Delta\) values).

4. The Mask Sub-Challenge

Firstly, we present our experimental results on the Mask Sub-Challenge. For classification, we employed SVM with a linear kernel, using the libSVM implementation \[30\]; the value of \(C\) was set in the range \(10^{-3}, 10^{-1}, \ldots, 10^4\). To combine the different approaches, following our previous works, we decided to take the weighted mean of the posterior estimates; the weights were set on the development set, with 0.05 increments.

Our results achieved can be seen in Table 2. By using the ‘ComParE functionals’ feature set we got a slightly better UAR score (at least, on the development set) than what was reported in the baseline paper (i.e. 62.6% \[19\]), but it is probably due to the different SVM implementation used (i.e. libSVM instead of scikit-learn); on the other hand, Bag-of-Audio-Words led to a quite similar classification performance (i.e. 64.2% vs. 64.5%). Unfortunately, using the temporal parameters turned out to be much less beneficial: the 50.6% UAR score measured on the development set is only slightly higher than what is achievable by random guessing.

When combining the approaches, the temporal parameters were not really useful either: fusing them with the ‘ComParE functionals’ predictions actually brought an insignificant improvement (0.01%); furthermore, the ComParE + BoAW combination was also only slightly better than any individual method (i.e. cca +1%). Fusing the ComParE functionals with those of the Fisher vectors, however, led to an efficient machine learning model, achieving an UAR value of 68.1% on the development set. Adding the Bag-of-Audio-Words and the temporal feature sets to this combination did not help the prediction significantly on the development set; or, according to our submissions, they even decreased the UAR values. While the ComParE + FV variation achieved a 72.0% on the test set, even slightly outperforming the official baseline score (which was obtained by a combination of models based on their test set performance), we got 71.6% and 71.8% in the other two cases. This, in our opinion, indicates that the Fisher vector representation approach was quite robust on the Mask Sub-Challenge; on the other hand, the temporal attributes were not really useful. Bag-of-Audio-Words, on the other hand, were found to be quite sensitive to meta-parameters, and are, in general, less robust than either ComParE functionals or Fisher vectors \[37\].

5. The Elderly Emotion Sub-Challenge

This Sub-Challenge was quite different than either the Mask Sub-Challenge, or most sub-challenges in the past years. The reason for this is that the organizers provided features based on the transcription of the utterances; but since these make sense only for larger utterances than the standard few-seconds-long chunks, predictions have to be submitted for recordings being several minutes long. Unfortunately, this also meant that the training, development and test sets all consisted of 87-87 (albeit long) utterances. Another, although minor difference was the presence of the two subtasks (i.e. arousal and valence).

On the technical level, this affected some parts of our the classification framework as well. We decided to discard the chunks provided by the organizers, and we focused on the longer recordings (which we reconstructed by simply merging the 5-second-long chunks). To compensate for the significantly less examples, we used 10-fold (speaker-independent) cross-validation for meta-parameter setting instead of relying on the provided development set; test set predictions were made with the same SVM models. On the other hand, to meet the Challenge guidelines, we repeated all experiments with the provided train-dev setup.

Similarly to the Mask Sub-Challenge, we used the same libSVM implementation (with the same \(C\) values tested). On the other hand, as the distribution of the Low, Medium and High

| Approach                          | Dev    | Test   |
|----------------------------------|--------|--------|
| Temporal parameters              | 50.6%  | 71.8%  |
| ComParE functionals              | 64.2%  | 71.8%  |
| Bag-of-Audio-Words               | 64.5%  | 71.8%  |
| Fisher Vectors                   | 67.7%  | 71.8%  |
| ComParE + Temporal               | 64.2%  | 71.8%  |
| ComParE + BoAW                   | 65.8%  | 71.8%  |
| ComParE + FV                     | 68.1%  | 72.0%  |
| ComParE + BoAW + FV              | 68.5%  | 71.8%  |
| All four attribute sets          | 68.6%  | 71.6%  |
| Best single method in \[19\] (test)| 63.4%  | 70.8%  |
| ComParE 2020 baseline \[19\]     | 71.8%  |        |

Table 2: Results for the Mask Sub-Challenge
class labels was somewhat imbalanced, we decided to opt for downsampling. Since downsampling shrinks our already small training sets even further, we decided to repeat SVM training 100 times for each training fold; therefore, for each feature set and for each \( C \) value, we trained 1000 models. Model fusion was done by simply taking the (unweighted) mean of the predicted posterior values.

Our results can be seen in Table 3. First, notice that the CV and the development set-level UAR scores not always display the some tendencies. In our opinion, this is due to the extremely small-sized corpus: having only \( 3 \times 87 \) utterances carries the risk to be insufficient even to allow measuring the classification performance reliably. (Of course, this comes from the attempt to provide BERT embeddings as features, which make sense only for larger utterances.) Unfortunately, this also means that setting the meta-parameters of the different methods might prove to be challenging, which actually coincides with our experience. During our experiments, we found that optimal meta-parameters (and the corresponding accuracy / UAR values) which we set on the classic “training set + development set” set-up differed greatly from those set in ten-fold cross-validation.

Regarding the arousal values, all tested approaches were proven to be useful even alone to achieve a competitive performance; however, among them, the temporal parameters and the Fisher vectors seem to be the most effective techniques. For valence, however, the linguistic attributes (i.e. the BERT embeddings) seem to be unmatched: no other method was able even to come close to the 49.1% (development set) and the 64.0% (cross-validation) UAR scores. It is logical, though, as the other approaches are all acoustic ones, and therefore not really suitable to detect valence.

### 6. Conclusions

For our contribution to the Interspeech 2020 Computational Paralinguistics Challenge, first we experimented with features derived from speech tempo. Our motivation was that emotion is reported to be related articulation tempo (i.e. the number of phones uttered per second), and it affects the amount of hesitation as well. To this end, we employed ASR techniques and extracted articulation rate, speech tempo and further 12 attributes describing the amount of hesitation in the utterance. According to our experimental results on the development set, this attribute set is not really useful for detecting whether the speaker is wearing a surgical mask, as the UAR score of 50.6% attained is only slightly above the change achievable via random guessing; on the other hand, in the arousal subtask of the Elderly Emotion Sub-Challenge it led to similar UAR values as the other methods described in the baseline paper.

Besides these custom features, we also applied standard methods like Bag-of-Audio-Words and Fisher vectors, and combined our predictions with those got by using the standard ‘ComParE functionals’ attribute set and in the case of the Elderly Emotion Sub-Challenge, the various BERT embeddings. These methods and their combinations proved to be quite useful on the development sets, but for the Mask Sub-Challenge we even managed to outperform the official baseline score, which itself is also a combination of four approaches.

For the Elderly Emotion Sub-Challenge, we found the tested temporal attributes helpful for the arousal task; for valence, however, they were less useful. In general, the low number of training, development and test instances made Elderly Emotion a particularly challenging task; in the end, we managed to obtain a mean UAR score of 50.5%, but this is probably not much higher than what could be achievable by random guessing (and saving the fifth submission to pair up the best arousal and valence “predictions”).

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\(^2\) No pun intended.
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