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Speaker Adaptation for Support Vector Machine based Word Prominence Detection

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Abstract

In this paper we propose a new speaker adaptation method to improve the detection of prominent words in speech. Prosodic cues are difficult to extract, due to the different features different speakers are using to express, for example prominence. To overcome the problem of variation from the pool of speakers used during training and those encountered during deployment, in speech recognition speaker adaptation techniques like fMLLR turned out to be very useful. In the case of prominence detection, our results have shown that a discriminative classifier like SVM works better than GMM. Existing adaptation methods like fMLLR are developed for GMM-HMM based classifiers under the assumption that the data has a Gaussian distribution. This does not hold for our data, using the fMLLR with the SVM leads not to an improvement for our problem area.
Therefore we propose a new adaptation method, which adapts the data to the RBF kernel of the SVM, subsequently regularizing it with the fMLLR. We investigate how this method can be used to adapt a new speaker to a speaker independent model for word prominence detection. We show that the error rate improves from the speaker adaptation from 16.4% to 14.4%.
Index Terms: prosody, speaker adaptation, fMLLR, SVM

1. Introduction

Prosody plays an important part in human communication. One part of this is the determination of the prominence of a word. If we want to highlight a word as important, e.g. to indicate a correction, this can be achieved by increasing the prominence of the word [1, 2]. Even though speech is getting more important in human-machine communication, and integrating this information could improve the performance, prosody has been rarely used in spoken dialog systems so far [3, 4]. The reason might be that prosodic cues are difficult to extract and that there is a large variation between different speakers.
Therefore, it is not surprising that speaker dependent trained classification schemes work better than speaker independent trained ones. WSpeaker dependent trained models have the drawback that they need a high amount of labeled data to train such a model. This makes them very inconvnient to real applications. Instead of training a new model, especially for a new speaker, but achieving a comparabel accuracy, we are using the speaker independent system and adapting it with a small amount of speaker dependent data. Speaker adaptation is an established method in speech processing. Thereby, adaptation methods often used are maximum likelihood linear regression (MLLR) [5] and maximum a posteriori (MAP) [6]. However until now only a few works have employed these techniques for the adaption of prosodic features. One [7] proposes a system which adapts to a drivers voice for emotion recognition in the automotive environment. The adaptation is accomplished in the acoustic space by mean and standard deviation normalization. Another work [8] used a combination of MAP and Gaussian mixture models (GMM) for an unsupervised adaptation to a new unlabeled data set. But since that, to our knowledge, not much research has been done and there is no other work which uses speaker adaptation methods like fMLLR for detection of prosody and especially not for support vector machines.
Compared to the work of [8] we investigate an adaptation that is independent of the classifier. Prominence detection is a two class problem with highly overlapping classes. Therefore prior experiments show that support vector machines (SVM) are a better choice for the classification than e.g. a Gaussian mixture model based classification. For our first experiments we chose for adaptation the feature-space maximum likelihood linear regression over the in speech processing more common model-based methods like MLLR and MAP, since the feature space variant is in principle independent from the classifier. The fMLLR can therefore be also used in combination with SVM. Our results show that the adaptation works in combination with the GMM but does not improve the classification of the SVM. One reason is that the assumption of a Gaussian distribution does not fit our data, an other might be that fMLLR does not incorporate any discriminative information. Therefore in this paper we propose a new method, based on the radial basis function parameters, which are used in the trained SVM model to incorporate the information of the decision boundary in the adaptation. For better results we subsequently regularize the method with the fMLLR.
The next section will present the database used, followed by a description of the audio features in section 3. Afterwards, we give a short overview of the adaptation methods in section 4: the fMLLR (4.1) followed by our new method, the feature-space SVM adaptation (4.2) and the fMLLR regularized SVM adaptation (4.3). Following a short description of the SVM implementation in section 5 is the presentation of the results in section 6. We will conclude with a discussion of our findings in section 7 and a subsequent conclusion in our final section.

2. Data set

The audio-visual data was recorded as a Wizard-of-Oz experiment during a small game where the subjects moved tiles to

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uncover a cartoon [9]. The subjects had to give spoken advice, in a simple grammar, to a computer, such as: "place green in B one". Some of the words were misunderstood by the machine; this was verbally and visually shown. Then the subjects had to correct the sentence by repeating it and using prosodic cues to emphasize the misunderstood word as they would do with a human listener. However, correcting cue phrases such as "no I said" were not allowed. This procedure should lead to a rather natural use of prosody, creating a narrow focus condition (in contrast to the broad focus condition of the original utterance) with the corrected words marked as highly prominent.
For the experiment a subset of 8 subjects, male and female, speaking either British or American English as native language or being either bilingual in British English/German or American English/German were recorded. Over 2500 utterances with 4 to 5 words each where used for evaluation. For the experiments in this work we used only the audio recordings. The speech was recorded with a distant microphone at 48 kHz and later downsampled to 16 kHz. A speech recognition system trained on the Grid Corpus [10] was used for forced alignment.
Three human annotators rated the recorded data with a 4 level scale (0-3) of prominence for each word. We calculated the inter-annotator agreement with Fleiss' kappa κ. While doing so we binarized the annotations, only differentiating between prominent and non-prominent. A word was annotated as prominent if the mean rating of all annotators was above 1.5. During the annotation we saw that on the one hand, not all speakers consistently used prominence to highlight the corrected word and, on the other hand, that for some speakers the annotators were not able to come to a consensus on the prominence of the words. Therefore, from the original 16 speakers we retained 8 which showed an agreement measured with Fleiss' κ of more than 0.55 between all annotators ($0.4< \kappa <0.6$ is usually considered as moderate agreement). Of this eight subjects, two are female and six male, two speak American English (including one being bilingual in American English/German) and six speak British English (including two being bilingual in British English/German).

3. Features

For the detection of word prominence we employ the prosodic features which have been previously proposed to correlate with word prominence. The beginning and end of the word is taken from the forced alignment and used to calculate the duration of a word as well as the gap length before and after the word.
The loudness is calculated by first filtering the signal with an 12th order IIR filter following the ideas outlined in [11], followed by calculating the instantaneous energy, smoothing with a low pass filter with a cut-off frequency of 10 Hz, and finally converting the results to dB. We expected the loudness to better capture the perceptual correlates of prominence than the energy.
As described in [12], we extract the fundamental frequency f_0 (following [13]), interpolate values in the unvoiced regions via cubic splines and convert the results to semitones. To detect voicing we use an extension of the algorithm described in [14].
Another feature we use is the spectral emphasis i.e. the difference between the overall intensity and the intensity in a dynamically low-pass-filtered signal with a cut-off frequency of 1.5 f_0 [15].
From the fundamental frequency, energy and loudness, we extract functionals as described in [13] for a better prosodic analysis. We extract the mean, max, min, spread (max-min) and variance along the word. Prior to the calculation of the functionals we normalize the prosodic features by their utterance mean and calculated their first and second derivative. To model the contour we calculate the DCT features from the features and retain the first 10 coefficients.
Marking the focus of a word in an utterance rendering it prominent also has an influence on the neighboring words. Modifying the articulatory parameters to raise the prominence of a segment of an utterance (hyperarticulating) is usually accompanied by a reduction of these parameters (hypoarticulation) for the neighboring segments [16, 17]. It has previously been shown that taking this context information into account is very effective for the detection of word prominence and pitch accents [18, 19, 20]. Therefore, we take not only the functionals of the current word itself for classification but also those of the previous and the following word (see [18] for details).
Considering all audio features with its functionals and context features we obtain an feature vector with a dimension of 159.

4. Adaptation methods

In this section we first give a short description of the well-known fMLLR, followed by the introduction of our proposed new method which is based on the SVM model with radial basis function model and the method regularized by the fMLLR.

4.1. Feature-space MLLR

The first adaptation method we are using is the feature-space Maximum likelihood linear regression (fMLLR) [5]. Compared to MLLR, which transforms mean and variance of an HMM-model, it transforms the features directly and is hence independent of the classifier and can be used in combination with e.g. SVMs. The calculation of the adaptation matrix we use the row-by-row updates for adaptation matrices [21]. The transformation matrix $\mathbf{W}$ consists of a affine matrix $\mathbf{A}$ and a bias vector $\mathbf{b}$:

$$\hat{\mathbf{x}} = \mathbf{A}\mathbf{x} + \mathbf{b} = \mathbf{W}\xi, \tag{1}$$

where $\xi = [\mathbf{1}\ \mathbf{x}^\mathbf{T}]^\mathbf{T}$ is the input vector extended with an extra element equal to unity. The transformation matrix is calculated by optimizing the auxiliary function:

$$\begin{aligned}\mathcal{Q}_{\text{ML}} &= \sum_{t,m}^{T,M} \gamma_\mathbf{m}(\mathbf{t})[\log \mathcal{N}(\mathbf{W}\xi_\mathbf{t}, \mu_\mathbf{m}, \mathbf{\Sigma_m}) + \log(\mathbf{A})] \\ &= \log|\det(\mathbf{A})| \\ &\quad - \frac{1}{2}\sum_{t,m}^{T,M} \gamma_\mathbf{m}(\mathbf{t})(\mathbf{W}\xi_\mathbf{t} - \mu_\mathbf{m})^\mathbf{T}\mathbf{\Sigma}_\mathbf{m}^{-\mathbf{1}}(\mathbf{W}\xi_\mathbf{t} - \mu_\mathbf{m}),\end{aligned}$$

with $\mathbf{\Sigma}$ and μ being the statistics of the training data and the posterior probability γ of sample $\mathbf{x_t}$ being in Gaussian m. M is the number of mixtures and T the number of samples. We use the supervised version for adaptation, taking a small labeled subset of the test data for adaptation. Therefore, we use the same amount of prominent and non-prominent samples to calculate the transformation matrix.
We also experimented with different numbers of Gaussian mixtures, but taking more than one per class did not improve the results.

4.2. Feature-space Adaptation to SVM boundary

Since the data seems to be not well represented by a Gaussian mixture model and the fMLLR is not entirely suitable for

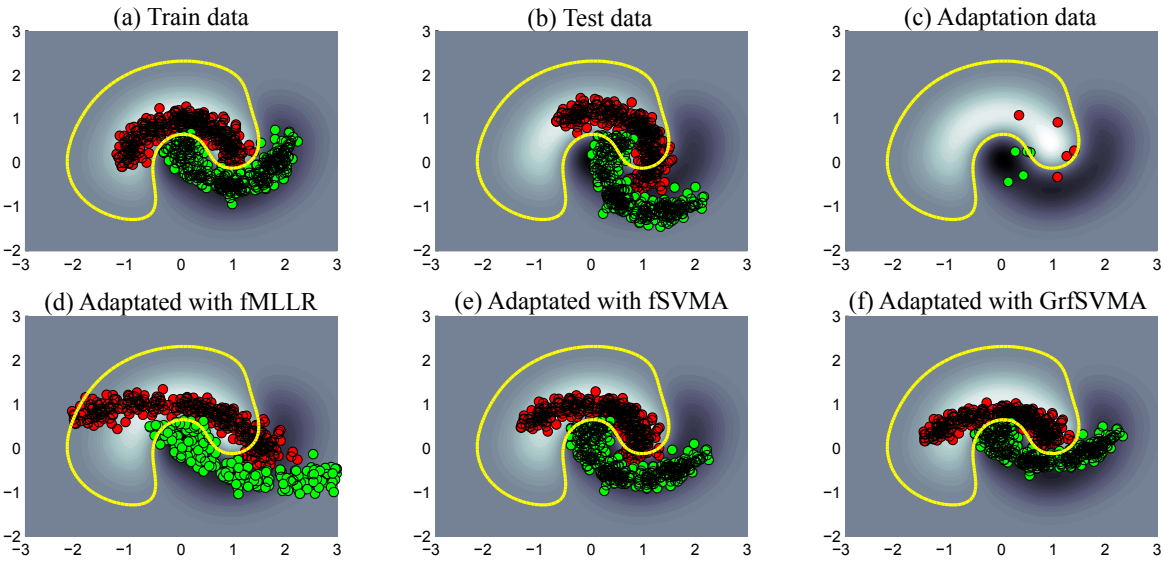

Figure 1: (a) Training data, (b) test data, (c) adaptation data, (d) data after Transformation calculated with fMLLR, (e) data after Transformation calculated based on SVM model, fSVMA, (f) data after Transformation calculated with the GrfSVMA .

a discriminative classifier, we propose to adapt the data more directly to the trained SVM model, the feature-space Support Vector Machine Adaptation (fSVMA). For calculating the SVM model we use the radial basis function kernel (RBF). The RBF is defined through the support vectors $\mathbf{s}_i$ and the scale parameter γ_{SVM}. So the function we want to optimize for calculating the transformation matrix $\mathbf{W}$ is now as follows:

$$\mathcal{Q}_{\text{SVM}} = \sum_{t}^{T} \sum_{n}^{N} y_t \alpha_n e^{(-\gamma_{\text{SVM}} \|\mathbf{W}\xi_\mathbf{t} - \mathbf{s_n}\|^2)}, \qquad (2)$$

with the parameters from the learned SVM model, α_i being the weights, y_i the class affiliation, and N the number of support vectors. The function is optimized by using gradient descent.

4.3. feature space MLLR regularized SVM Adaptation

A transformation matrix that fits the adaptation data to the decision boundary will probably tend to overfit. Therefore, we propose to regularize the SVM adaptation with the fMLLR, in order to get a tradeoff between the fitting of the adaptation data to the SVM boundary and the more general fitting to the assumed Gaussian distribution. We call this method feature space MLLR regularized SVM Adaptation (GrfSVMA). In the new optimization function the regularization term is weighted by λ:

$$\mathcal{Q}_C = \mathcal{Q}_{\text{SVM}} + \lambda \mathcal{Q}_{\text{ML}}. \qquad (3)$$

This combined term is also optimized by using gradient descent.

To illustrate how the adaptations are working we show the transformation results using the example of the two dimensional classification problem from [22] with two intertwining moon distributions, each belonging two a specific class. Fig.1 demonstrates the two classes (green/red) as well as the SVM decision boundary (yellow). (a) shows the data used for training, while (b) shows the slightly shifted and rotated (45°) data for testing. This example presents a case where an adaptation would be useful but the Gaussian assumption does not fit. Especially the estimation of the variance is difficult, if only a small amount of adaptation data (c) is available. The sub images (d), (e) and (f) shows the test data after transformation with the fMLLR, the fSVMA and the GrfSVMA ($\lambda = 1$). The corresponding classification results can be found in Tab.1. It is obvious that the adaptation with fMLLR brings only small gain while there is a risk that the data is stretched to much. The fSVMA as well as the GrfSVMA work quite well and can reach nearly the same performance as the training data.

(a)	(b)	amount of adaptation data per class	(c)	(d)	(e)
0.5%	16.1%	5	12.9%	1.8%	3.4%
		10	5.2%	1.2%	2.9 %

Table 1: Error for classification with the training data (a), test data (b), adapted data with fMLLR (c), fSVMA (d) and GrfSVMA (e).

5. Classification

As mentioned before, for problems such as the word prominence detection, discriminative classifiers proved to be a good choice, we use a classification with support vector machines (SVM). Therefore, we used the libsvm implementation [23] with a radial basis function kernel. Furthermore, for the parameter C, the penalty parameter of the error term, and the variance scaling factor γ of the basis function, a grid search on the whole data set was performed.

In order to use the adaptation we determined mean and variance of the training data, scaled them to zero mean and unit variance and than used the same scaling factors for the test and the adaptation data. We experimented with full covariance matrices [24], but it is a well-known problem that the estimation of the covariance matrix with a small amount of adaptation data is difficult, especially with less data per class than dimensions [25]. So on the one hand, we did a feature reduction with a PCA transformation taking only the first 79 dimensions, because dis-

	speaker dependent	speaker independent
GMM	17.1%	22.0%
SVM	11.5%	16.4%

Table 2: Speaker dependent vs. speaker independent classification with SVM and GMM for prominence detection: unweighted error rate average over all speakers.

carding the 80 higher dimensions did not change the performance of the SVM. On the other hand we assumed a diagonal covariance matrix for the training and the adaptation data.

6. Results

Because the two classes, prominent and non-prominent, are highly unbalanced - approx. one times to nine - the accuracy is not a good measure to compare the results. A preference of non-prominent words would always lead to very good accuracy but would not provide an objective evaluation. Consequently, the unweighted error rate is used instead.

$$\begin{aligned} \text{precision} &= \frac{tp}{tp+fp}, \\ \text{specificity} &= \frac{tn}{tn+fp}, \\ \text{unweighted error} &= 1 - \frac{\text{precision} + \text{specificity}}{2}, \end{aligned}$$

with tp: true positive, fp: false positive and tn: true negative. In order to better understand the possible gain of the speaker adaptation, we will first show the performance difference between the speaker dependent and speaker independent classification. For speaker independent classification the model is trained on 7 speakers and tested on the last (leave-one-speaker-out classification). For speaker dependent classification the data is divided in a training set, containing 75% of the data, and a test set, containing the remaining 25% of the data, using a 30 fold cross validation in which the data set is always split in a way that the same number of elements is taken from both classes was run. Tab.2 shows the results for speaker dependent classification compared to the speaker independent classification with SVM and GMM. The average unweighted error rate over all speakers for speaker dependent training is 11.5% for SVM and 17.1% for GMM. If we have a speaker independent classification the result for the averaged unweighted error rate increases to 16.4% respectively 22%. Tab.3 now shows the results for the speaker independent classification for the different adaptation techniques. We considered 40 data points per class for the adaptation. Former experiments have shown that it is hard to represent this high dimensional data with less adaptation data. The weighting parameter λ of the GrfSVMA is, after testing different values, set to 1 to give both parts an equal weight. Without adapting, the classification error is 16.4% for SVM and 22.0% for GMM. Using the fMLLR did improve the results for the GMM classification from 22.0% to 20.4% but not for the SVM classification. Therefore, for the SVM, using only the fSVMA, the error did increase. But for the regularized version of the method we got an improvement of 2% absolute to 14.4%. However, using instead the same adaptation data in addition to the training data to retrain the model, shows only very small improvement since the amount of adaptation data is very small compared to around 10000 original data points for training.

	(a)	(b)	(c)	(d)
GMM	22.0%	20.4%	-	-
SVM	16.4%	16.3%	29.2%	14.4%

Table 3: Error for classification with the test data (a), adapted data with fMLLR (b), and fSVMA (c) and GrfSVMA (d).

7. Discussion

Due to the high inter-speaker variations the unweighted error rate averaged over all speakers drops from 11.2% for speaker dependent to 16.2% for speaker independent training, although the amount of training data is much higher for the independent model. Therefore, an adaptation should be useful. The standard fMLLR works for GMM, but since the overall results for SVM are better than GMM with adaptation, an adaptation method which is able to improve the SVM classification is desirable.
The two-dimensional example of the moon shaped distribution showed that for the case of a classification with SVM for data that is not Gaussian distributed, the standard adaptation method fMLLR is not the best choice. Our method which uses the information of the decision boundary could get a much higher performance, even with a low amount of adaptation data.
For our real data the classification is much more complex due to the high dimension and the overlapping classes. Using fMLLR with 40 data points per class to calculate the transformation matrix, did not lead to a notable improvement for SVM. A small amount of adaptation data, compared to the high dimension, seems not to be able to give a good representation of the statistics of the data. Therefore we assume that the reason is that the data is not well described by a Gaussian model. Using only the adaptation to the SVM boundary, the fSVMA, did increases the error. The reason might be that, with the small amount of adaptation data, we had a strong overfitting to the adaptation data. However, the GrfSVMA which uses the information about the boundary and avoids overfitting by regularize the transformation through the fMLLR did lead to an relative improvement of 12.2% from 16.4% to 14.4%.

8. Conclusion

In this paper we have presented a new method for speaker adaptation developed for a SVM classifier with RBF kernel. To our knowledge there hasn't been any work using common speaker adaptation methods like fMLLR for the detection of prosodic features; especially, not in a classification with SVM. For problems where a discrimintative classifier like SVM works best but the Gaussian distribution assumption does not hold, like in the case of speaker independent prominence detection, the standard method for speaker adaptation is not the best choice. We have shown that our method generally works well for an example like the moon shaped distribution. In the case of the word prominence detection where only little adaptation data is available in comparison to the feature dimensionality, the adaptation to the decision boundary leads to an overfitting. Nevertheless, we were able to show that the regularization of our method through the fMLLR leads to an improvement from 16.4% to 14.4% error rate, corresponding to a relatve improvement of 12.2%.

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10. References

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