COMBINING CATEGORICAL AND PRIMITIVES-BASED EMOTION RECOGNITION

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ABSTRACT
This paper brings together two current trends in emotion recognition: feature-based categorical classification and primitives-based dynamic emotion estimation. In this study, listeners rated a database of acted emotions using the three-dimensional emotion primitive space of valence, activation, and dominance. The emotion primitives were estimated by a fuzzy logic classifier using acoustic features. The evaluation results were also used to calculate class representations of the emotion categories happy, angry, sad, and neutral in the three-dimensional emotion space. Speaker-dependent variations of the emotion clusters in the 3D emotion space were observed for happy sentences in particular. The estimated emotion primitives were classified into the four classes using a kNN classifier. The recognition rate was 83.5% and thus significantly better than a direct classification from acoustic features. This study also provides a comparison of estimation errors of emotion primitives estimation and classification rates of emotion classification.

1. INTRODUCTION
Emotion recognition in speech plays an important role in man-machine-interaction and provides enriched descriptions for content and style-based speech data mining. In many cases, it is not only important, what a person says, but also how it is expressed. In recent years, the main focus of emotion recognition has been on the classification of utterances into a few coarse emotion categories, such as happy, neutral, sad, angry [1, 2]. In a valence-appraisal approach only binary emotion recognition has been studied, e.g. negative vs. non-negative [3, 4], or negative vs. positive [5]. There are some studies on how to represent emotions in a multi-dimensional emotion space (see Cowie [6] for an overview, [7, 8]). One powerful representation is in terms of the three emotional attributes (“primitives”) namely valence (positive vs. negative), activation (excitation level high vs. low), and dominance (apparent strength or weakness of the speaker) [7].

In this paper we investigate the relations between categorical emotion classes and their realization in the three-dimensional emotion space. We present both a rule-based estimation system of the emotion primitives from acoustic features and a mapping from this three-dimensional emotion space to conventional emotion categories. For some applications, individual emotion class probabilities are required, such as for instance, user frustration detection. For time-continuous emotion tracking, however, it is more reasonable to estimate generic emotion components. The benefit of clustering in the emotional primitive space is that such clustering lends itself to categorical emotion estimation while at the same time providing a basis for gradual and continuous automatic assessment of emotions.

To our knowledge, this paper reports on the first study that provides a direct comparison of categorical emotion recognition rates in terms of classical confusion matrices on the one hand, and emotion estimation errors expressed by distance measures in the 3D emotion space on the other hand.

Fig. 1. System for categorical and dimensional emotion recognition described in this paper.

The rest of the paper is organized as follows. Section 2 introduces the data we use. Section 3 describes both the human evaluation of emotional speech in a categorical way and in terms of the three emotion primitives. Section 4 presents details of estimating the three-dimensional emotion primitives from speech using a rule-based fuzzy logic classifier, and de-
For this study, we used the EMA Corpus conclusions and outlines future work. acoustic features to emotion classes. Section 5 draws some results are compared to those achieved by directly classifying human listeners, averaged over all speakers and all sentences. riving subsequent mapping to the emotion classes. The results are compared to those achieved by directly classifying acoustic features to emotion classes. Section 5 draws some conclusions and outlines future work.

2. DATA
For this study, we used the EMA Corpus [9]. In total, it contains 680 sentences of emotional speech, produced by one professional (f) and two non-professional (1f/1m) speakers. The female speakers produced 10, and the male speaker produced 14 sentences, each in the 4 different emotions happy, angry, sad, and neutral with 5 repetitions each [9]. All sentences are in English, spoken by native American English speakers. The sampling frequency was 16 kHz, with 16 bit resolution.

3. EMOTION EVALUATION

3.1. Categorical emotion evaluation
The EMA database was evaluated by 4 native speakers of American English. They chose between the emotions happy, angry, sad, neutral, and other. On average, 81.8% of the acted emotions were recognized by the listeners. Table 1 shows the averaged confusion matrix of all three speakers in the database.

The evaluator agreement, corrected for chance agreement, was measured using the kappa statistics [10] with \( \kappa \in [0, 1] \). In our case, we got \( \kappa = 0.48 \) indicating moderate to high evaluator agreement.

<table>
<thead>
<tr>
<th></th>
<th>Angry</th>
<th>Happy</th>
<th>Neutral</th>
<th>Sad</th>
<th>Other</th>
</tr>
</thead>
<tbody>
<tr>
<td>Angry</td>
<td>80.3</td>
<td>2.2</td>
<td>4.1</td>
<td>0.7</td>
<td>12.7</td>
</tr>
<tr>
<td>Happy</td>
<td>3.2</td>
<td>75.6</td>
<td>11.8</td>
<td>1.3</td>
<td>8.1</td>
</tr>
<tr>
<td>Neutral</td>
<td>1.2</td>
<td>0.4</td>
<td>84.0</td>
<td>11.8</td>
<td>2.6</td>
</tr>
<tr>
<td>Sad</td>
<td>0.3</td>
<td>0.6</td>
<td>6.3</td>
<td>87.5</td>
<td>5.3</td>
</tr>
</tbody>
</table>

Table 1. Confusion matrix of emotion class labeling of EMA corpus, in percent, by four human listeners (\( \kappa = 0.48 \)).

<table>
<thead>
<tr>
<th></th>
<th>Valence</th>
<th>Activation</th>
<th>Dominance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Std. deviation</td>
<td>0.35</td>
<td>0.36</td>
<td>0.35</td>
</tr>
<tr>
<td>Correlation coeff.</td>
<td>0.63</td>
<td>0.79</td>
<td>0.75</td>
</tr>
</tbody>
</table>

Table 2. Standard deviation \( \sigma \) and correlation coefficient \( r \) for the emotion primitives evaluation of the EMA corpus by 18 human listeners, averaged over all speakers and all sentences.

As a counterpart to the categorical classification confusion matrix above, the standard deviation of the evaluations was calculated. On average over all 680 sentences, it was between 0.35 and 0.36 for all all primitives; see Tab. 2 for details. The evaluators show moderate to high inter-evaluator agreement as can be derived from Pearson’s correlation coefficient. On average, the correlation coefficient between an evaluator’s rating and the mean value of all other evaluators was 0.63, 0.79 and 0.75 for valence, activation, and dominance, respectively. Agreement on valence was not as high as on the other dimensions, c.f. Tab. 2. This might be due to the overall more narrow distribution of valence values in the database resulting in a greater effect for disagreement on particular sentences. In the following, only those 614 sentences (90%) of the EMA database were used that had been evaluated with a deviation of not more than one manikin. Thereby, the average standard deviation was slightly reduced to 0.34, 0.36, and 0.34, respectively.

3.2. Three-dimensional emotion evaluation
We adopt the appraisal-power concept of emotion space from Kehrein [7] using the three dimensions of emotion attributes valence, activation, and dominance. The EMA corpus was evaluated by 18 evaluators along the three dimensions. For emotion assessment, a text-free evaluation tool based on Self Assessment Manikins (SAMs) [11] was used. For each of the emotion components, the evaluators had to choose one out of five given iconic images depicting the level of the attribute. In contrast to [11], we chose the axes scaled to the range \([-1, +1]\). For better comparison, they are oriented from negative to positive (valence), from calm to excited (activation), and from weak to strong (dominance).

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3.3. Emotion classes in three-dimensional emotion space
To study the relationship between emotion categories and their location in emotion space, we analyzed the three-dimensional evaluation of the EMA database for each emotion separately. Fig. 2 shows the emotion space distri-
emotion distributions for each class for all three speakers as a result of 18 evaluator’s decisions. Angry was found to be very negative, very excited and very strong. Happy was moderately positive and excited. Neutral in our database was moderately negative, and moderately calm and weak, showing the greatest values of standard deviation. These speaker-dependent neutral values could be used as a baseline for the emotion recognition. Sad was found to be negative, calm and weak, forming an antipode to happy.

The emotion evaluation using the primitives also reveals why the human listeners’ recognition of the category happy was worse than other categories (c.f. Tab. 1): The perceived values of valence are only moderately positive (c.f. Fig. 2, second row, left column).

We calculated the centroids and the covariances for each emotion class. As a result of the 3D emotion space evaluation, each class was found to be concentrated in an individual subspace of the emotion space. Since activation and dominance were highly correlated ($r = 0.9$), Fig. 3 shows the projection of the $2\sigma$-regions on the valence-activation plane. The high correlation might be due to the selected emotions in this database (e.g. there was no fear emotion which would probably have positive activation but negative dominance values).

The centroids and covariances for each emotion class varied for different speakers, as shown in Fig. 3. In particular, the happy sentences were perceived significantly different for the individual speakers. The average values of the class centroids are given in Tab. 3.

We compared these results to values found in the literature [12, 8]. Cowie et al. use a 2D evaluation-activation space [12], while Schröder et al. use a 3D evaluation-activation-power space [8]. They derive their results from evaluation tests using the Feeltrace tool [13] and an additional word lexicon for the power values. Apart from neutral, which they define to be (0,0,0), the results are similar but not identical, c.f. Tab. 3. The differences might be caused by the different data and evaluation systems used. To our knowledge, the values given in Tab. 3 are the first comparable results achieved by the use of the text-free emotion evaluation method based on SAMs.

### Table 3. Comparison of emotion class centroids in the 3D emotion space.

<table>
<thead>
<tr>
<th>Emotion</th>
<th>Valence</th>
<th>EMA corpus</th>
<th>Schröder et al.$^1$</th>
<th>Cowie et al.$^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Valence</td>
<td>Activation</td>
<td>Evaluation Power</td>
<td>Evaluation Activation</td>
</tr>
<tr>
<td>Angry</td>
<td>-0.35 ± 0.17</td>
<td>0.46 ± 0.18</td>
<td>-0.35 0.35 -0.34</td>
<td>-0.70 0.65</td>
</tr>
<tr>
<td>Happy</td>
<td>0.31 ± 0.17</td>
<td>0.16 ± 0.15</td>
<td>0.40 0.29 0.13</td>
<td>0.54 0.48</td>
</tr>
<tr>
<td>Neutral</td>
<td>-0.16 ± 0.09</td>
<td>-0.32 ± 0.09</td>
<td>0 -0 -0</td>
<td>0 0</td>
</tr>
<tr>
<td>Sad</td>
<td>-0.43 ± 0.12</td>
<td>-0.57 ± 0.13</td>
<td>-0.43 -0.09 -0.55</td>
<td>-0.80 -0.15</td>
</tr>
</tbody>
</table>

$^1$Original values in the range [-100,+100] were scaled to the range [-1,+1] for comparison (c.f. Tab. 3 in [8]).

$^2$Given values were read from Fig. 3 in [12] and are only approximate.

![Fig. 3. Emotion classes in the valence-activation plane, as a result of the 3D attribute evaluation. For each of the 3 speakers, 4 emotion subspaces are shown as calculated from the mean values of all 18 evaluators.](image)

### 4. EMOTION CLASSIFICATION

#### 4.1. Categorical emotion classification

For comparison, we performed a direct emotion classification based on the 46 features extracted from the acoustic signal. The feature vector dimension was reduced to 17 using PCA and an eigenvalue threshold of 0.01. As a classifier we implemented a Mahalanobis distance classifier using the covariance matrices calculated from the training data. On average, the recognition rate of this multiple classification task was 54%. Using a $k$-Nearest Neighbor ($k$NN) classifier and a Euclidean distance measure improved the recognition rate to 58% ($k = 5$). We chose the same classifier for the mapping from 3D emotion estimates to emotion classes (Sec. 4.3).
Table 4. Emotion estimation error and correlation results using fuzzy logic, mean values for all speakers. The references are the average evaluator rating (EV) and the class centroids (CC), respectively.

<table>
<thead>
<tr>
<th></th>
<th>Valence</th>
<th>Activation</th>
<th>Dominance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Error $\bar{e}$</td>
<td>0.21 0.21</td>
<td>0.17 0.15</td>
<td>0.18 0.17</td>
</tr>
<tr>
<td>Correlation $\bar{r}$</td>
<td>0.67 0.70</td>
<td>0.89 0.90</td>
<td>0.85 0.87</td>
</tr>
</tbody>
</table>

Table 5. Confusion matrix of emotion classification from three-dimensional emotion components using a $k$NN classifier ($k = 7$).

### 4.2. Three-dimensional emotion estimation

We use a fuzzy logic inference system to estimate the three emotion attributes from speech features. Fuzzy logic was also applied in the emotion recognition context by Lee et al. [15] and Huang et al. [16], but not to estimate the aforementioned 3 emotion components. Fuzzy logic is a reasonable choice because of the fuzzy nature of emotion description and perception [16].

The rules in our inference engine are derived from the correlation between the acoustic features and the emotion reference as described in Sec. 3.2. The greatest correlation coefficients are found between energy features as well as some spectral features and activation and dominance ($r > 0.8$). Correlation to valence varies significantly for the different speakers.

For the fuzzy logic system, we use 3 membership functions for both input and output. Each acoustic feature is processed to membership grades of the linguistic variables low, medium, and high. Valence is represented by the linguistic variables negative, neutral, and positive. Similarly, activation is represented by calm, neutral, and excited. Dominance is represented by weak, neutral, and strong. For each linguistic input feature variable we define 3 rules that relate the fuzzy input variables to the fuzzy output variables. The details of aggregation, implication and defuzzification are reported in [14]. As a result of the defuzzification we get one estimate for each of the emotion primitives. We scale the results by a constant factor of 1.64 to map the range of the defuzzification output, [-0.61, +0.61], to the initial range of [-1, +1]. Fig. 4 shows the estimates, projected onto the valence-activation plane.

The emotion estimates were compared to the emotion reference. We considered two different references, (1) the evaluators’ mean rating, taken individually for each sentence (EV), and (2) the class centroids of the underlying acted emotion as computed in Sec. 3.3 (CC). Overall, we observed a mean error of 0.28 when compared to either the evaluators’ mean or the speaker-dependent class centroids, as computed above. The details for each emotion component are shown in Tab. 4.

The mean correlation between the emotion estimates and the reference was 0.80 when the reference was the evaluators’ rating, and 0.82 when the reference was given by the class centroids. The details for each emotion component are also reported in Tab. 4. These results indicate a low estimation error compared to the standard deviation achieved by human labeling. The correlation between estimates and reference is high. Probably the estimation results for the class centroids as a reference are better because the evaluators’ agreement is only moderate, c.f. Tab. 2.

### 4.3. Emotion classification from the three-dimensional estimates of emotion primitives

As a final step, we classified the three-dimensional emotion attribute estimates into the 4 emotion classes. This procedure allows for a comparison of the calculated estimation errors to “classical” recognition rates. For classification we used a Mahalanobis distance-based classifier and the class centroids and covariances as calculated in Sec. 3.3. An average recognition rate of 73.3% was achieved for the classification of 4 emotions. Using a $k$NN classifier (with Leave-One-Out cross validation) improved the results significantly. The mean recognition rate was 83.5% using the best parameter set of $k = 7$ and the 3D emotion estimates based on the evaluator ratings (EV). The recognition rate was 81.2% when the 3D emotion estimates were based on the class centroids (CC). The confusion matrix of the best results is shown in Tab. 5. The classification errors are mainly due to neutral - sad mis-
classifications. These reflect the estimated class distributions (c.f. Fig. 4) and the confusion seen in the listeners’ evaluations.

5. CONCLUSION AND OUTLOOK
In this paper we investigated the feasibility of emotion recognition based on three primitive attributes, valence, activation and dominance. We compared classification based on continuous characterization of emotional attributes to direct classification into emotion categories. The 3D emotion estimation is particularly suited for time-continuous emotion estimation of natural, and therefore value-continuous, emotions. Using a database of acted emotions angry, happy, neutral, and sad we demonstrated the performance of the 3D emotion recognition method.

The standard deviation of 3D evaluation was found to be moderately low (σ = 0.35), where the range of value of the primitives was [-1, +1]. The correlation between different evaluators was moderate to high (0.6 < r < 0.8). We showed that the emotion classes form separable subspaces in the emotion primitive space, as a function of the speaker. The significant speaker-dependency in the centroids of the emotion class happy, e.g., stresses the fact that just one category label for all “happy” utterances is not enough to capture emotion intensities or dynamics.

The 3D emotion components were automatically estimated using a fuzzy logic inference system. On average, the estimation error was 0.28 and thus even slightly below the evaluators’ standard deviation. The correlation to the reference was higher than human agreement (0.7 ≤ r ≤ 0.9). Both assessment and estimation was better for activation and dominance than for valence.

For comparison, the 3D estimates were classified into the four emotion classes, achieving a recognition rate of 83.5%. This was significantly higher than a direct classification of the acoustic features into four classes. Note that both classifiers were distance-based kNN classifiers. Since for our data with defined emotion categories we calculated the estimation error and the recognition rate, these results can serve as a rule of thumb for future research on authentic emotions of spontaneous speech, where it is not possible to calculate emotion recognition rates due to the gradual nature of authentic emotions.

There are many applications which would benefit from estimating gradual variation of emotion values as presented in this study. The estimation of emotion primitives lends itself to dynamic representations of emotions and the ability to adapt the emotion baseline to individual speakers.

In future work, both the speaker dependency and the listener (evaluator) dependency of emotion should be considered in the classification methods. More sophisticated features and classifiers will further improve the recognition results.

6. ACKNOWLEDGMENT
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7. REFERENCES