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## ABSTRACT

We examine the robustness of several audio features applied exemplarily to musical instrument classification. For this purpose we study the robustness of 15 MPEG-7 Audio Low-Level Descriptors and 13 further spectral, temporal, and perceptual features against four types of signal modifications: low-pass filtering, coding artifacts, white noise, and reverberation. The robustness of the 120 feature coefficients obtained is evaluated with three different methods: comparison of rankings obtained by feature selection techniques, qualitative evaluation of changes in statistical parameters, and classification experiments using Gaussian Mixture Models (GMMs). These experiments are performed on isolated notes of 14 musical instrument classes.

## 1. INTRODUCTION

Automatic content analysis is an important challenge due to the ever-growing amount of multimedia data. Specifically, the content analysis of the audio part [1] of multimedia data is often based upon audio classification systems that need efficient features. In the past, the contribution of various audio features to high classification accuracy was examined in several research works. However, the robustness of audio features against signal modification in respect of the influence on the classification accuracy of classification systems has been widely neglected.

In contrast to other works dealing with classification of musical instruments [2–6], we concentrate in this paper on evaluating the robustness of a large number of audio features against signal modifications of the original audio data hence choosing the musical instrument classification scenario exemplarily as a first concrete classification problem.

The motivation is that such modifications are very common. In fact, the audio signal is often modified intentionally during the professional process of music creation (e.g. equalization or reverberation) or is modified by psychoacoustically motivated lossy audio codecs like MP3. There has been an attempt to study the robustness of a specific set of audio features by Sigurdson et al.[7], who examined the robustness of Mel-Frequency Cepstral Coefficients (MFCCs) for MP3 coding with different bit rates and sampling frequencies. They used several different implementations for MFCC extraction and utilized a correlation measure for the evaluation of robustness. In this work, we consider both more varied signal modifications and a wider set of features. We have chosen to study low-pass filtering, lossy audio coding/decoding, additive white Gaussian noise (AWGN), and reverberation as signal modifications since they are mostly independent from each other and common in real world applications.

The audio features used in this work are 15 MPEG-7 Audio Low-Level Descriptors and 13 other spectral, temporal, and perceptual features with different dimensionalities. Isolated notes of 14 different musical instruments of four classical instrument families are used as audio data. The robustness of features is evaluated with feature selection techniques, statistics, and classification experiments with GMMs. A *robust feature ranking* is created by combining all feature selection rankings from all signal modifications and the original audio signals. In particular, the best 5 and 13 features of the robust feature ranking are compared to the first 5 and 13 MFCCs in regard to classification accuracy.

The paper is organized as follows. Feature extraction and selection are briefly described in Section 2 and 3, respectively. The method for the creation of a robust feature ranking is proposed in Section 4. The experimental results are presented in Section 5, which is followed by conclusions and further work.

## 2. FEATURE EXTRACTION

The audio signal with a sample frequency of 44.1 kHz is divided into mostly overlapping blocks with a hop size of 10 ms, whereas the block size $T_B$ depends on the specific feature (in the range of 10 ms–30 ms). For instance the spectral MPEG-7 descriptors Audio Spectrum Envelope (ASE), Audio Spectrum Centroid (ASC), and Audio Spectrum Spread (ASS) use a blocksize of 30 ms to obtain a higher frequency resolution. For spectral features, a Short-Time Fourier Transform (STFT) with a Hamming window is applied to each block. The 15 extracted MPEG-7 Audio Low-Level Descriptors [8] could be generally divided into: basic temporal, basic spectral, temporal timbre, spectral timbre, and signal parameter descriptors listed in detail in Table 1. Especially, LAT is an important descriptor of typical onset times of musical instruments since it captures the logarithmic duration from signal start to the maximum or begin of the sustained signal

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| Descriptor | Label | Dim | $T_B$ | Category |
|---|---|---|---|---|
| Audio Waveform | AWF | 2 | 10 | BT |
| Audio Power | AP | 1 | 10 | BT |
| Audio Spectrum Envelope | ASE | 34 | 30 | BS |
| Audio Spectrum Centroid | ASC | 1 | 30 | BS |
| Audio Spectrum Spread | ASS | 1 | 30 | BS |
| Audio Spectrum Flatness | ASF | 24 | 10 | BS |
| Log Attack Time | LAT | 1 | 10 | TT |
| Temporal Centroid | TC | 1 | 10 | TT |
| Harmonic Spectrum Centroid | HSC | 1 | 30 | TS |
| Harmonic Spectrum Deviation | HSD | 1 | 30 | TS |
| Harmonic Spectrum Spread | HSS | 1 | 30 | TS |
| Harmonic Spectrum Variation | HSV | 1 | 30 | TS |
| Spectral Centroid | SC | 1 | 30 | TS |
| Audio Harmonicity | AH | 1 | 10 | SP |
| Audio Fundamental Frequency | AFF | 1 | 10 | SP |

Table 1: Overview of extracted MPEG-7 Audio Low-Level Descriptors (Dim - dimensionality, $T_B$ - blocksize in ms, BT - basic temporal, BS - basic spectral, TT - timbre temporal, TS - timbre spectral, SP - signal parameter)

| Feature | Label | Dim | $T_B$ | Category |
|---|---|---|---|---|
| Specific Loudness | Ld | 24 | 20 | PS |
| Sharpness | Sh | 1 | 20 | PS |
| Spread | Sp | 1 | 20 | PS |
| Mel Freq. Cepstral Coeff. | MFCC | 13 | 20 | PS |
| Zero Crossing Rate | Z | 1 | 20 | PT |
| Spectral Centroid | Sc | 1 | 20 | S |
| Spectral Width | Sw | 1 | 20 | S |
| Spectral Asymmetry | Sa | 1 | 20 | S |
| Spectral Flatness | Sf | 1 | 20 | S |
| Frequency Cutoff | Fc | 1 | 20 | S |
| Spectral Decrease | Sd | 1 | 20 | S |
| Spectral Oscillation | So | 1 | 20 | S |
| Spectral Slope | Ss | 1 | 20 | S |

Table 2: Overview of other extracted features (Dim - dimensionality, $T_B$ - blocksize in ms, PS - perceptual spectral, PT - perceptual temporal, S - spectral)

part. The other extracted audio features [9] could be generally divided into: temporal, perceptual spectral, and other spectral features. They are shown in Table 2. All these features result in a 120-dimensional feature vector. They are extracted from both the original sounds and all the sounds altered by the considered modifications.

The motivation for the chosen signal modifications is given in Section 1. The parameters of all considered signal modifications are listed in Table 3. It should be noted that the signal modifications are applied to each audio signal without changing the sample frequency.

## 3. FEATURE SELECTION

Feature selection techniques [10, 11] aim at obtaining a subset of efficient features from a larger set of candidate ones, where efficiency is determined by a chosen criterion. In general, the purpose of feature selection for classification problems is to maximize the classification accuracy. These techniques can be distinguished into filter and wrapper techniques. Filter techniques obtain their selection decisions

| Label | Parameter | Value | Unit | Description |
|---|---|---|---|---|
| **O** | - | - | - | original |
| **L8** | $f_c$ | 8 | kHz | low-pass filtering |
| **L16** | $f_c$ | 16 | kHz | low-pass filtering |
| **M32** | Bitrate | 32 | kb/s | MP3 cod./dec. |
| **M64** | Bitrate | 64 | kb/s | MP3 cod./dec. |
| **M128** | Bitrate | 128 | kb/s | MP3 cod./dec. |
| **N30** | SNR | 30 | dB | AWGN |
| **N40** | SNR | 40 | dB | AWGN |
| **R1** | RevTime<br>Delay | 2000<br>1000 | ms<br>ms | reverberation |
| **R2** | RevTime<br>Delay | 2000<br>800 | ms<br>ms | reverberation |
| **R3** | RevTime<br>Delay | 1500<br>750 | ms<br>ms | reverberation |

Table 3: Overview of signal modifications with parameters

from criteria computed with the initial features, whereas the feature selection decisions of wrapper techniques are directly based on the classification accuracy result. In this work, we consider two sequential filter techniques based on a Fisher-like criterion [11] and using two alternative subset search techniques known as sequential forward selection (SFS) and sequential backward selection (SBS). Since the rankings of SFS and SBS obtained from our experiments have only minor differences at the last rank positions, we will only consider further the SFS algorithm and rankings. The objective measure for the SFS algorithm [11]

$$J = \frac{\mathrm{Tr}(S_b)}{\mathrm{Tr}(S_w)} \tag{1}$$

is chosen in this work as a ratio between the trace of the between-class scatter matrix $S_b$ and the trace of the within-class scatter matrix $S_w$. $\mathrm{Tr}(S_b)$ is a measure of the average distance (over all classes) of the mean of each class from the global mean for all classes. $\mathrm{Tr}(S_w)$ is a measure for the average of variance of features. Therefore $J$ measures the separability of classes for a given set of features. Great between-class spacing and small within-class variances lead to high class separability (high values of $J$).

The SFS algorithm generates a ranking of features ordered by the highest class separability according to $J$ in the following way: $J$ is initially computed for each individual feature. The best feature (the one with the highest $J$) is first chosen. Subsequently, $J$ is computed for all pairwise combinations with the first rank feature and all other remaining features. The combination with the highest separability is chosen and the first two ranks are determined. These two ranks build a new subset and the SFS algorithm proceeds with the computation of $J$ for all combinations between this subset and one of all remaining features. Then again, the combination with the maximum $J$ is chosen and the next rank is determined. The SFS proceeds this way until the number of features that have to be selected is reached or the subset equals the set of available features. In the following, the algorithmic form of the SFS algorithm is presented. $\mathscr{X}$ is the set of all features.

| Rk | O | L8 | L16 | M32 | M64 | M128 | N30 | N40 | R1 | R2 | R3 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **1** | LAT | LAT | LAT | LAT | LAT | LAT | LAT | LAT | LAT | LAT | LAT |
| **2** | MFCC-3 | MFCC-3 | MFCC-3 | **Ld-2** | MFCC-3 | MFCC-3 | MFCC-3 | MFCC-3 | MFCC-3 | MFCC-3 | MFCC-3 |
| **3** | Ld-2 | Ld-2 | Ld-2 | **MFCC-3** | Ld-2 | Ld-2 | **MFCC-4** | **MFCC-4** | Ld-2 | Ld-2 | Ld-2 |
| **4** | MFCC-4 | MFCC-4 | MFCC-4 | MFCC-4 | MFCC-4 | MFCC-4 | **Ld-1** | **Ld-2** | MFCC-4 | MFCC-4 | MFCC-4 |
| **5** | Ld-1 | Ld-1 | Ld-1 | Ld-1 | Ld-1 | Ld-1 | **Ld-2** | Ld-1 | **ASC** | **ASC** | **ASC** |
| **6** | ASC | ASC | ASC | ASC | ASC | ASC | **MFCC-5** | ASC | **Ld-1** | **Ld-1** | **Ld-1** |
| **7** | MFCC-5 | **TC** | MFCC-5 | **TC** | **TC** | MFCC-5 | **ASC** | **TC** | MFCC-5 | MFCC-5 | MFCC-5 |
| **8** | TC | **Sc** | TC | **HSC** | **MFCC-5** | TC | TC | **MFCC-5** | TC | **HSC** | TC |
| **9** | Sh | Sh | Sh | Sh | **MFCC-6** | Sh | **ASE-34** | **MFCC-6** | Sh | **TC** | Sh |
| **10** | SC | **HSC** | SC | SC | **HSC** | SC | **MFCC-6** | SC | **Fc** | **Sh** | **Fc** |
| **11** | MFCC-6 | **MFCC-5** | MFCC-6 | **Sc** | **SC** | MFCC-6 | **SC** | **AWF-2** | MFCC-6 | **Fc** | MFCC-6 |
| **12** | Sa | **SC** | **Sc** | **Fc** | **Sh** | Sa | **MFCC-1** | **MFCC-7** | **SC** | **MFCC-6** | **SC** |
| **13** | Fc | **MFCC-6** | **Sa** | **MFCC-6** | **Sa** | Fc | **AWF-2** | **MFCC-1** | **HSC** | **SC** | **Sa** |

Table 4: Rankings of the 13 best features selected by SFS for original signals and all signal modifications. Features that differ from the ranking of the original signals (column **O**) are indicated bold.

| Rk | Feature |
|---|---|
| **1** | LAT |
| **2** | MFCC-3 |
| **3** | Ld-2 |
| **4** | MFCC-4 |
| **5** | Ld-1 |
| **6** | ASC |
| **7** | TC |
| **8** | MFCC-5 |
| **9** | MFCC-6 |
| **10** | SC |
| **11** | Sh |
| **12** | HSC |
| **13** | AWF-2 |

Table 5: The 13 best features of the robust feature ranking obtained by the average feature rank over all available modified audio databases and the original one for each feature.

1. Start with the empty feature set $\mathscr{Y}_s = \{\emptyset\}$ with $s = 0$.
2. Out of the features that have not yet been chosen, select the one feature $f^+$ that maximizes the objective function $J$ in combination with the previously selected features: $f^+ = \underset{f_i \in \mathscr{X} - \mathscr{Y}_s}{\operatorname{argmax}} \{J(\mathscr{Y}_s \cup f_i)\}$.
3. Update: $\mathscr{Y}_{s+1} = \mathscr{Y}_s \cup f^+$, $s \rightarrow s+1$.
4. Go to 2.

## 4. ROBUST FEATURE RANKING

How is it possible to identify robust features or obtain a robust feature ranking for audio features automatically? To this end, we propose the following scheme. Various signal modifications should be introduced by applying various audio effects to an initial "clean" database of audio classes. Feature selection techniques are then applied to the original and each such modified audio database. Here, the feature selection process can be stopped if the desired dimensionality is reached. The feature ranking for the original database along with the rankings for all modified databases are subsequently combined in a straightforward way. The robust feature ranks are ordered according to the average rank for each feature where the average is computed over all available modified databases and the original one.

## 5. EXPERIMENTAL RESULTS

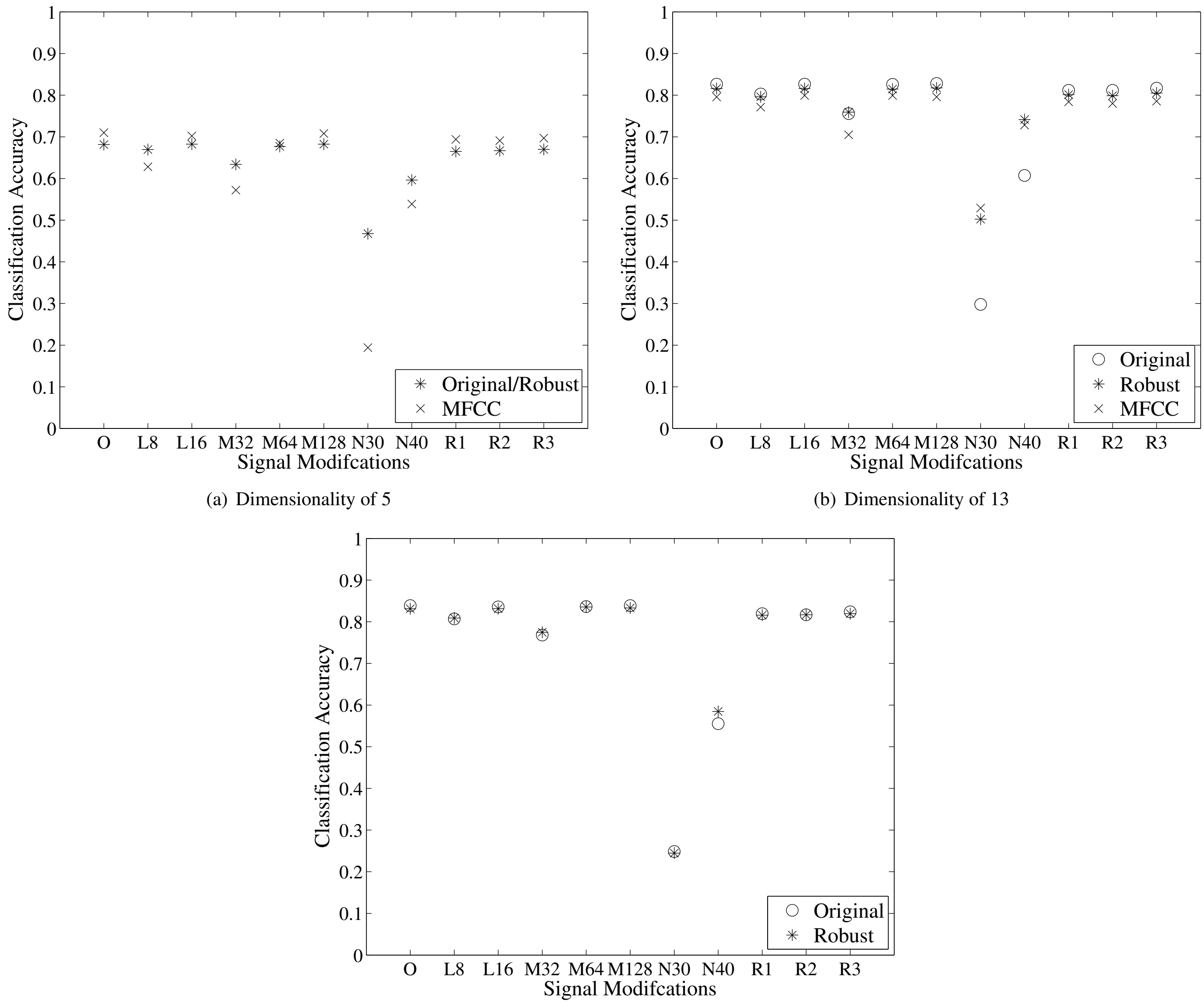
Approximately 6000 isolated notes of 14 different musical instruments with different pitch and playing styles are used as audio data. The instruments are woodwinds (bassoon, clarinet, horn, flute, oboe), brass (tuba, trombone, trumpet, sax), strings (contrabass, cello, viola, violin), and piano. The audio data is part of the Musical Instrument Sound Database (RWC) [12].

After feature extraction, a feature ranking is created for each signal modification and the original audio data with SFS resulting in 11 rankings. The SFS is performed on approximately $10^6$ frames for each signal modification. The Table 4 lists the 13 best features for all signal modifications and the original audio data selected with SFS. Table 5 lists the 13 robust features that are selected by the average feature ranks over all effects as described in Section 4.

LAT has the highest class separability for all signal modifications and the original signals. The work by Simmermacher et al. [5] shows the same result for original audio data with different feature selection methods on isolated notes. Their study shows further that the results for musical instrument classification on isolated notes can not easily be generalized to solos. Hence, the results may not apply to the even more complex case of polyphonic music. Nevertheless, note that the principle of our approach is not restricted to isolated notes, nor to the music instrument classification problem.

For isolated notes, also some of the lower MFCCs, the first two perceptual adapted loudness coefficients (Ld-1 and Ld-2), the spectral centroids (SC and ASC) and the temporal centroid (TC) have low ranks for all signal modifications and the original signals. The deviation of feature ranks over the SFS rankings corresponding to different signal modifications is relatively low for these mentioned features.

Furthermore, the maximum, minimum, mean, median, standard deviation, skewness, and kurtosis of each feature over all classes and for all signal modifications and the original database are extracted to explore their changes. Great




(a) Dimensionality of 5

(b) Dimensionality of 13

(c) Dimensionality of 30

Figure 1: Classification accuracy for GMM classification experiments with original and robust features selected with SFS retaining the first 5, 13, and 30 features as well as MFCC for 5 and 13 features.

variations of the statistics of a feature over the different signal modifications suggest that this feature is highly influenced by this signal modifications and thus not very robust. The features LAT and TC show very small changes of their statistics, so the statistical evaluation supports the results of the robust feature ranking in Table 5. This features could be considered as very robust features. Some of the lower MFCCs and the first two Ld coefficients (Ld-1 and Ld-2), SC, and ASC show some larger differences between the statistics for additive noise, so they could be considered as some less robust features for noise, although they are among the 13 best features of the robust feature ranking, but they seem to be robust against all other signal modifications.

After evaluating the feature rankings, the classification accuracies of the robust feature scheme are compared to the ones relating to a classification scheme based on features selected over the original database and to a third classification scheme using only MFCCs, as these are very common audio features. Since the robust features and the selected features of the original database do not differ for the dimensionality of 5, they are compared jointly to the first 5 MFCCs. For a dimensionality of 13, robust and original feature selections are compared to the first 13 MFCCs. For a dimensionality of 30, only the robust features are compared to the original feature selection.

Gaussian Mixture Models (GMMs) [11] are used as parametric models for maximum likelihood (ML) classification. So a joint decision for all frames of each isolated note is taken to classify the musical instrument. The GMMs for each class of musical instrument have eight Gaussian components. They are trained with the well-known Expectation Maximization (EM) algorithm. For the training phase, we choose to exploit only features extracted from the original audio data to put the focus on the contribution of a *robust feature selection* stage to the classification performance. All classification experiments are performed with ten-fold cross-validation. Results in terms of average classification accuracies are shown in Figure 1.

The results of the classification experiments show us that mainly lossy audio compression with low bit-rates (M32) and additive white Gaussian noise (N30 and N40) as signal modifications affects the classification accuracy. For low dimensionality, we obtain the result that normal feature selection on original audio data lead to the same set of features as the robust feature ranking for the given audio classes and signal modifications. Therefore, the obtained classification accuracies for the set of features selected from the original database are valid at the same time for the robust feature ranking. The set of the first five MFCCs could be outperformed for L8, M32, N40, and N30. Especially for N30, the gain in classification accuracy with feature selection compared to the first five MFCCs is approximately 27 %. For a dimensionality of 13, the robust feature set can improve the classification accuracy up to 20 % for N30 compared to the original feature selection. Here, it is remarkable, that only two features of the original feature selection are replaced. Namely, Sa (Spectral Asymmetrie) and Fc (Frequency Cutoff) are replaced by HSC (Harmonic Spectrum Centroid) and AWF-2 (positive envelope).

For a higher dimensionality such as 30, it seems that features, which are highly affected by signal modifications such as noise, are again among the set of features that are supposed to be robust. However, the robustness is also a matter of the dimensionality and the available initial set of features. We observe that the greater number of 30 selected features (see Figure 1(c) compared with Figure 1(b)) leads to lower classification accuracies for N30 and N40. The classification accuracies for all other signal modifications and the original signals does not change significantly.

Furthermore the differences in accuracies between the features based on original audio data and the robust features are very small for all signal modifications. Using only a fixed set of features such as the first 13 MFCCs instead of using any feature selection technique at all can by chance lead to a robust classification system as Figure 1(b) shows for N30 and N40.

The proposed robust feature selection method is mostly useful when the feature dimensionality is very limited (as Figure 1(a) and Figure 1(b) show). Finally, the experimental results show us in the main that our scheme to construct a robust set of features based on standard feature selection techniques is successful.

## 6. CONCLUSIONS AND FUTURE WORK

An evaluation of robust audio features against common signal modifications has been performed. For this purpose a method for the creation of a robust feature set has been proposed. The successful improvement of the classification accuracy for modified signals has been proven in an experimental evaluation. Further work will extend this method to more complex databases with solos or even polyphonic music as well as to other classification problems. Also we will consider training the classifiers on both the original and modified audio data. Beyond features of frames, audio texture windows capturing long-term properties should be considered further.

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