COMPARISON OF SUBSPACE ANALYSIS-BASED AND STATISTICAL MODEL-BASED ALGORITHMS FOR MUSICAL INSTRUMENT CLASSIFICATION

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ABSTRACT

In this paper, three classes of algorithms for automatic classification of individual musical instrument sounds are compared. The first class of classifiers is based on Non-negative Matrix Factorization, the second class of classifiers employs automatic feature selection and Gaussian Mixture Models and the third is based on continuous Hidden Markov Models. Several perceptual features used in general sound classification as well as MPEG-7 basic spectral and spectral basis descriptors were measured for 300 sound recordings consisting of 6 different musical instrument classes (piano, violin, cello, flute, bassoon, and soprano saxophone) from the University of Iowa database. The audio files were split using 70% of the available data for training and the remaining 30% for testing. Experimental results are presented to compare the classifier performance. The results indicate that all algorithm classes offer an accuracy of over 95% that outperforms the state-of-the-art performance reported for the aforementioned experiment.

1. INTRODUCTION

The need for analysis of musical content arises in different contexts and has many practical applications, mainly for effectively organizing and annotating data in multimedia databases, automatic music transcription and internet search. Automatic musical instrument classification is the first step in developing the above systems, a research area which can be also applied in general sound recognition applications. However, despite the massive research which has been carried out on a similar field, namely automatic speech recognition, limited work has been done on musical content identification systems.

Experiments carried out so far operate on various number of instruments and classes and are separated into two categories: classification of isolated instrument tones, and classification of sound segments. Classifiers using only isolated tones have a limited use in a practical application, while sound segment classifiers could be effectively used in Music Information Retrieval (MIR) systems. Using sound segments, Brown reported correct identifications of 79-84% for four classes of instruments, using Bayes decision rules for classification [10]. Cepstral coefficients, constant-Q coefficients and autocorrelation coefficients were used as features to audio files derived from the same database used in the present paper (MIS Database from UIOWA [1]). More recently, Synak et al [11] used MPEG-7 temporal descriptors and various spectral features for sound segments consisting of 18 instrument classes and developed 2 classifiers, the first using the k-NN algorithm and the second using decision rules based on the theory of rough sets, achieving at best 68.4% recognition rate.

In our work, the problem of automatically classifying musical instrument segments is addressed. Files derived from the UIOWA database [1] were used, forming 6 instrument classes. Two algorithm classes for classification are compared. The first algorithm class is based on Non-negative Matrix Factorization (NMF) [5], a subspace method for basis decomposition. A novel application for NMF is provided, since this method has been mainly used in face recognition applications and several proposed NMF modifications were applied. The second classifier class is based on the parametric estimation of a Gaussian Mixture Model (GMM) using long-term feature processing and automatic feature selection [12]. The feature selection algorithm used is the Sequential Forward Selection Algorithm, which selects the optimal features from the feature set, maximizing class separability. The third class uses a system based on continuous Hidden Markov Models (HMMs), as described in [4]. For feature extraction, features used in general audio classification experiments were used along with spectral descriptors proposed by the MPEG-7 audio standard [2]. For the first classifier class, a set of 4 extracted features was used, while the second class used an extended feature set. The results indicate that using the standard NMF algorithm, the automatic feature selection system using GMMs or the HMM-based system leads to a classification accuracy of over 95%.

The remainder of this paper is organized as follows. The audio feature sets used are discussed in Section 2. Section 3 describes the NMF method, its numerous extensions and the classification system. Section 4 presents the GMM-based classifier and the feature selection algorithm utilized. Section 5 presents the HMM-based system. Section 6 describes the data set used alongside the experimental results, and Section 7 concludes the paper.

2. FEATURE EXTRACTION

In an audio classification system a careful selection of features that are able to accurately describe the temporal and spectral sound structures is vital. In our approach, three different feature sets were used for the two classifier classes. In Table 1, 3 features describing timbral texture were used along with the MPEG-7 AudioSpectrumProjection coefficients for the NMF algorithms.

For the second classifier class, an extended feature set was

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Table 1. Feature set used for NMF classifiers.

1	Zero-Crossing Rate
2	Delta Spectrum
3	Spectral Rolloff Frequency
4	MPEG-7 AudioSpectrumProjection Coefficients

used for automatic feature selection. The extracted features, which are presented in Table 2, describe signal energy (features 1-4), timbral texture (features 5-9), spectral and harmonic characteristics as defined by the MPEG-7 audio standard (features 10-13), and temporal features (features 14-16). Finally, the third algorithm class was based only on Mel-Frequency Cepstral Coefficients (MFCCs).

Table 2. Feature set used for GMM-based classifiers.

1	RMS Energy
2	Low Energy Rate
3	Loudness
4	Predictivity Ratio
5	Zero-Crossing Rate
6	Spectral Roll-off Frequency
7	Delta Spectrum
8	Mel-Frequency Cepstral Coefficients
9	Spectral Centroid
10	MPEG-7 AudioSpectrumCentroid
11	MPEG-7 AudioSpectrumSpread
12	MPEG-7 AudioSpectrumFlatness
13	MPEG-7 Harmonic Ratio
14	The maximum of the time-domain audio signal
15	Skewness of the time-domain audio signal
16	Kurtosis of the time-domain audio signal

3. A SYSTEM BASED ON NON-NEGATIVE MATRIX FACTORIZATION ALGORITHMS

Non-negative Matrix Factorization (NMF) [5] is a novel subspace method in order to obtain a parts-based representation of objects, by imposing non-negative constraints. The problem imposed by NMF is as follows: Given a non-negative $n \times m$ matrix V (data matrix), find non-negative matrix factors W and H in order to approximate the original matrix:

$$V \approx WH \tag{1}$$

where the $n \times r$ matrix W contains the basis vectors and the $r \times m$ matrix H contains the weights needed to properly approximate the corresponding column of matrix V, as a linear combination with the columns of W. Usually, r is chosen so that $(n+m)r < nm$, thus resulting in a compressed version of the original data matrix. To find an approximate factorization posed in (1), a suitable objective function has to be defined and the generalized Kullback-Leibler divergence between V and WH is most frequently used. Presented below are the various algorithms proposed for NMF, differing mainly in the constraints imposed in their according objective function.

The standard NMF enforces the non-negativity constraints on matrices W and H, thus a data vector can be formed by an additive combination of basis vectors. The proposed cost function is the generalized KL divergence:

$$D(V||WH) = \sum_{i=1}^{n}\sum_{j=1}^{m}[v_{ij}\log\frac{v_{ij}}{y_{ij}} - v_{ij} + y_{ij}] \tag{2}$$

where $WH = Y = [y_{ij}]$. $D(V||WH)$ reduces to KL divergence when $\sum_{i=1}^{n}\sum_{j=1}^{m} v_{ij} = \sum_{i=1}^{n}\sum_{j=1}^{m} y_{ij} = 1$. An NMF factorization is defined as:

$$\min_{W,H} \ D(V||WH) \quad subj.to \ W,H \geq 0, \sum_{i=1}^{n} w_{ij} = 1 \, \forall j \tag{3}$$

where $W, H \geq 0$ means that all elements of matrices W and H are non-negative. The above optimization problem can be solved by using the iterative multiplicative rules found in [5].

Aiming to impose constraints concerning spatial locality and consequently revealing local features in the data matrix V, the local NMF (LNMF) incorporates 3 additional constraints into the standard NMF problem:

1. Minimize number of basis components representing V.
2. Different bases should be as orthogonal as possible.
3. Retain components giving most important information.

The above constraints are incorporated into the cost function and its local minimization can be found by using 3 update rules found in [6].

Inspired by NMF and sparse coding, the aim of sparse NMF (SNMF) is to impose constraints that can reveal local sparse features on data matrix V. A SNMF factorization is defined the same as in (3), including also that $\forall i ||w_i||_l = 1$. In SNMF sparseness is measured by a linear activation penalty, the minimum l-norm of the column of H. A local solution to the above minimization can be found by the update rules in [7].

By improving on the NMF and the LNMF approaches, the discriminant NMF (DNMF) keeps the original constraints from the NMF algorithm, enhances the locality of basis vectors imposed in the LNMF algorithm and attempts to improve classification accuracy by incorporating into the above constraints information about class discrimination. Two more constraints are introduced:

1. Minimize the within-class scatter matrix $\mathbf{S}_w$.
2. Maximize the between-class scatter matrix $\mathbf{S}_b$.

Information on the update rules that find a local solution to the minimization of the cost function can be found in [8].

Musical instrument classification in the NMF subspace is performed as follows: using data from the training set, the data matrix V is created (each column $\mathbf{v}_j$ contains a feature vector computed from an audio file). Training is performed by applying an NMF algorithm into V, yielding the basis matrix W and the encoding matrix H.

In the test phase, for each test audio file (represented by a feature vector $\mathbf{v}_{test}$) a new test encoding vector is formed as:

$$\mathbf{h}_{test} = W^{\dagger}\mathbf{v}_{test} \tag{4}$$

where $W^{\dagger}$ is defined as the Moore-Penrose generalized inverse matrix of W. Having formed during training 6 classes of encoding vectors $\mathbf{h}_l$ (where $l = 1, ..., 6$), a nearest neighbor classifier is employed to classify the new test sample by using the Cosine Similarity Measure (CSM). The class label l' of the test file is defined as:

$$l' = \arg\max_{l=1,\ldots,6}\{\frac{\mathbf{h}_{test}^T\mathbf{h}_l}{||\mathbf{h}_{test}||||\mathbf{h}_l||}\} \tag{5}$$

thus trying to maximize the cosine of the angle between $\mathbf{h}_{test}$ and $\mathbf{h}_l$.

4. A SYSTEM BASED ON AUTOMATIC FEATURE SELECTION AND GAUSSIAN MIXTURE MODELS

The second system to be evaluated is based on the parametric estimation of a statistical model, in this case a Gaussian Mixture Model, for each of the training classes. It is a simplified, non-hierarchical version of the system that was presented and thoroughly evaluated in [12]. Its main characteristics are long-term feature processing and automatic feature selection. Long-term feature processing denotes that the individual feature vectors are not computed on a frame-by-frame basis, but are rather generated from the statistical analysis of short-time features across the whole audio file. Specifically, the mean and standard deviation from the variation in time of each feature, as well as from their derivatives, are computed for each file and collected into a single feature vector representing that particular file.

As described in Section 2, 16 features were used for extraction and afterwards selection, consisting of three groups. Applying the three statistical *subfeatures* mentioned, results in a total number of 64 dimensions. In order to avoid the *curse of dimensionality* phenomenon, which implies that too much dimensions can reduce the classification performance, a dimensionality reduction step is needed.

This is performed in the present system by means of an automatic feature selection algorithm, specifically, a Sequential Forward Selection Algorithm, which selects the combination of features that maximizes an objective criterion of class separability. This criterion is defined by

$$J = \frac{|\mathbf{S}_b|}{|\mathbf{S}_w|}. \tag{6}$$

The selection algorithm then consists of following steps:

1. Start with the empty feature set $\mathcal{V}_0 = \{\emptyset\}$.
2. Out of the features that have not yet been chosen, select the one feature f^+ that maximizes the objective function in combination with the previously selected features: $f^+ = \operatorname*{argmax}_{v_i \in \mathcal{X} - \mathcal{V}_s} \{J(\mathcal{V}_s \cup v_i)\}$.
3. Update: $\mathcal{V}_{s+1} = \mathcal{V}_s \cup v^+$, $s \rightarrow s+1$.
4. Go to 2.

The algorithm ends when the desired number of features has been reached.

Once the best features have been selected, a 3-density GMM is trained for each class using the Expectation-Maximization (EM) algorithm. This results in a set of conditional densities

$$p(\mathbf{v}|\omega_k) = \sum_{m=1}^{M} w_{km}\, p_{km}(\mathbf{v}) \tag{7}$$

where w_{km} are the weights of the mixture, M is the total number of densities in the mixture and p_{km} is a Gaussian density. According to the maximum likelihood criterion, the conditional density of an unknown feature vector is computed for all the classes, and the highest one is chosen and declared as the class it belongs to.

The fact that automatic feature selection is used implies that the system has the ability to easily adapt itself to several kinds of audio classification tasks. Although the system was initially tested as a speech/music/noise discriminator and as a music genre classifier [12], it is shown here that it can also be successfully used as a musical instrument classifier.

5. A SYSTEM BASED ON CONTINUOUS HIDDEN MARKOV MODELS

The third system is based on Mel-Frequency Cepstral Coefficient (MFCC) [13] features and continuous Hidden Markov Models (HMMs). A detailed description of that system and of the usage of cepstral features for sound and speaker recognition can be found in [4].

The feature extraction process consists of short-time Fourier transform (STFT) with the usage of Hamming window, band summation and Discrete Cosine Transform (DCT). The cepstral coefficients are extracted in the frequency range from 64 Hz to 16 kHz with 23 overlapped mel-warped triangular filters. The logarithmic frame energy and the five first MFCCs build the feature vector, resulting in a feature set which can be obtained very fast and efficiently.

The classification process is performed by a classifier based on HMMs with three emitting states in a left-right topology. The Baum-Welch algorithm [14] is used for training. For classifying sounds their features are presented to each of the HMMs. For computing the most likely state sequence for each model the Viterbi algorithm is used. The model with the maximum likelihood score determines the label for the analyzed sound.

6. EXPERIMENTS

For the experiments we used audio files taken from the MIS database developed by the university of Iowa [1]. Overall 300 audio files were used, consisting of 6 different instrument classes: piano, violin, cello, flute, bassoon and soprano saxophone. In detail, 58 files contain piano recordings, 101 violin recordings, 52 for cello, 31 for saxophone, 29 for flute and 29 for bassoon. The 300 sounds are partitioned into a training set of 210 sounds and a test set of 90 sounds, preserving a 70%/30% analogy between the two sets, which is typical for classification experiments. All data are at 44.1kHz sampling rate and with a duration of about 20sec long.

The classification experiments were made using 7-fold cross validation, for the four NMF algorithms described in Section 3, for the GMM-based system described in Section 4 and for the continuous HMM-based system in Section 5. For the GMM system, three experiments were performed, using 3, 20 and 40 features. The mean classification rate for all eight experiments along with the standard deviation is presented in Figure 1. Using the automatic feature selection algorithm, the three best features selected for the three GMM classification experiments are presented in Table 3.

Table 3. Best 3 features selected for GMM-based classification.

Experiment	Features
3 Features	St. Dev. of the 1st MFCC coefficient
20 Features	St. Dev. of the Derivative of the 1st MFCC coefficient;
40 Features	St. Dev. of the Derivative of the Spectral Centroid

The highest accuracy is achieved by the GMM classifier using 20 features, with 99.52% mean classification rate. Overall,

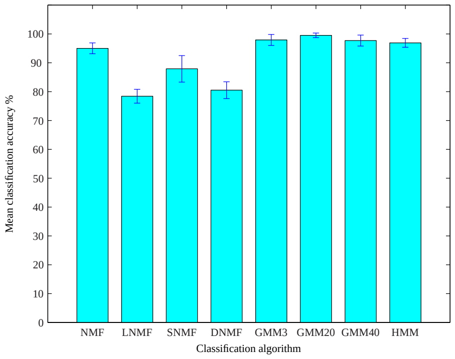

Fig. 1. Classification accuracy for the tested algorithms.

the systems with classification accuracy over 95% are the ones using Standard NMF, GMMs (all 3 experiments) and the HMMs. It should be noted that the LNMF, SNMF and DNMF algorithms perform classification with rates well below 95%, which indicates that parts-based descriptors are not suitable for classifying holistic descriptors, whereas the more holistic NMF classifier displayed satisfactory results. More detailed information about the performance of the various algorithms is shown in Tables 4, 5 and 6 in the form of a confusion matrix, where the columns correspond to the predicted musical instrument and the rows to the actual one. For the Standard NMF algorithm, most misclassifications occur for the flute, while for the HMM-based system other instruments are misclassified as cello. It can be seen in table 5 that for the GMM classifier using 20 features, no misclassifications occur.

Table 4. Confusion matrix for one pass of the Standard NMF.

Instr.	Piano	Bassoon	Cello	Flute	Sax	Violin
Piano	**18**	0	0	0	0	0
Bassoon	1	**8**	0	0	0	0
Cello	0	0	**16**	0	0	0
Flute	2	1	0	**6**	0	0
Sax	0	0	0	0	**9**	0
Violin	0	0	0	0	0	**29**

Table 5. Confusion matrix for one pass of the GMM with 20 features.

Instr.	Piano	Bassoon	Cello	Flute	Sax	Violin
Piano	**18**	0	0	0	0	0
Bassoon	0	**9**	0	0	0	0
Cello	0	0	**16**	0	0	0
Flute	0	0	0	**9**	0	0
Sax	0	0	0	0	**9**	0
Violin	0	0	0	0	0	**29**

7. CONCLUSIONS

In this paper, we have compared three systems for classifying musical instrument recordings, the first using subspace analysis and the other two utilizing statistical model-based algorithms. A variety of features used in audio classification experiments were used along with MPEG-7 descriptors. Results indicate that all three systems can perform classification with over 95% accuracy, outperforming state-of-the-art systems.

Table 6. Confusion matrix for one pass of the HMM.

Instr.	Piano	Bassoon	Cello	Flute	Sax	Violin
Piano	**18**	0	0	0	0	0
Bassoon	0	**9**	0	0	0	0
Cello	0	0	**16**	0	0	0
Flute	0	0	1	**8**	0	0
Sax	0	0	0	0	**9**	0
Violin	0	0	1	0	0	**28**

8. REFERENCES

[1] University of Iowa Musical Instrument Sample Database, http://theremin.music.uiowa.edu/index.html.

[2] MPEG-7 overview (version 9), *ISO/IEC JTC1/SC29/WG11 N5525*, March 2003.

[3] A. T. Lindsay, I. Burnett, S. Quackenbush, and M. Jackson, “Fundamantals of Audio Descriptors”, in *Introduction to MPEG-7*, (B.S.Manjuntath, P.Salembier and T.Sikora), pp. 285-298, Eds. New York: Wiley, 2000.

[4] H. G. Kim, N. Moreau, and T. Sikora, “Audio classification based on MPEG-7 spectral basis representations,” *IEEE Trans. Circuits and Systems for Video Technology*, vol. 14, no. 5, pp. 716-725, May 2004.

[5] D. D. Lee and H. S. Seung, “Algoritnms for non-negative matrix factorization,” *Advances in Neural Information Processing Systems*, vol. 13, pp. 556-562, 2001.

[6] S. Z. Li, X. Hou, H. Zhang, and Q. Cheng, “Learning spatially localized, parts-based representation,” in Proc. *IEEE Conf. Computer Vision and Pattern Recognition*, pp. 1-6, 2001.

[7] C. Hu, B. Zhang, S. Yan, Q. Yang, J. Yan, Z. Chen, and W. Ma, “Mining ratio rules via principal sparse non-negative matrix factorization,” in Proc. *IEEE Int. Conf. Data Mining*, 2004.

[8] I. Buciu and I. Pitas, “A new sparse image representation algorithm applied to facial expression recognition,” in Proc. *17th Int. Conf. Pattern Recognition*, August 2004.

[9] G. Tzanetakis and P. Cook, “Musical genre classification of audio signals,” *IEEE Trans. Speech and Audio Processing*, vol. 10, no. 5, pp. 293-302, July 2002.

[10] J. C. Brown, O. Houix, and S. McAdams, “Feature dependence in the automatic identification of musical woodwind instruments,” *J. Acoustical Society of America*, vol. 109, no. 3, pp. 1064-1072, March 2001.

[11] A. Wieczorkowska, J. Wroblewski, P. Synak, and D. Slezak, “Application of temporal descriptors to musical instrument sound recognition,” *J. Intelligent Information Systems*, vol. 21, no. 1, pp. 71-93, July 2003.

[12] J.J. Burred and A. Lerch, “Hierarchical automatic audio signal classification,” *J. Audio Engineering Society*, vol. 52, no.7, 2004.

[13] S. B. Davis and P. Mermelstein, “Comparison of parametric representations for monosyllabic word recognition in continuously spoken sentences,” *IEEE Trans. Acoust. Speech Signal Processing*, vol. 28, no. 4, pp. 357-366, 1980.

[14] L. R. Rabiner and B. H. Juang, “Fundamentals of speech recognition,” *Signal Processing Series*, 1993.