# Music Genre Classification Using Feature Subset Search

Jihae Yoon, Hyunki Lim, and Dae-Won Kim

*Abstract*—With the growing number of digital music, the automatic genre recognition problem has been receiving the spotlight in music retrieval information field. A large number of musical acoustic features are reported to degrade the genre classification performance and lead to heavy computational cost. In this paper, we propose a new method for selecting genre-discriminative feature subset from a large number of musical features. We show that the proposed method is able to improve the genre recognition accuracy compared to the traditional selection method.

*Index Terms*—Genre classification, feature selection, mutual information, incremental search.

### I. INTRODUCTION

For a long time, musical genre has been one of the most common description of music contents [1]. Generally human expertise manually annotates genre after listening the music [2]. These procedures require effort and time consuming. However, the suitability of genre annotated by human expertise depends on expertise's musical knowledge and previous experience [3]. With the explosive number of published digital music, an automatic genre recognition has been receiving the spotlight in music retrieval information (MIR) field [4].

Over the past year, many researchers have been employed for designing a learning algorithm that is able to identify the relationship between musical acoustic features and genre. For extracting musical features, many music analysis methods such as MIRtoolbox, JAudio and Marsyas are widely used [5], [6]. According to various options chosen by users, over the nine hundreds of musical features can be extracted from given music. However, all of features are not considered equally important in genre recognition. In some cases, irrelevant features degrade genre recognition performance and also lead to computational inefficiency. One straightforward solution is to select informative feature subsets from the large number of features.

Our goal is to identify a compact feature set that consists of genre discriminative features. The feature subset is found by incrementally searching informative features that take both of two notions, relevance and redundancy, into account. While the learning time is decreased by reduced number of features, the classification accuracy is improved than the case of all musical feature being involved in learning. From various tests, the present work to music genre classifications shows its potential and direction for improvement.

#### II. RELATED WORKS

In recent approaches to music genre recognition studies, there are two types of methods; the informative musical feature extraction and the classifier for constructing genre recognition model [7]. P. R. Lisboa de Almeida et al. proposed a dynamic ensemble approach to music genre recognition. They used a pool of classifiers consisted of weak classifier SVMs [8]. R. Popovici et al. proposed a method for genre classification using a self-organizing map (SOM) [9]. The method identifies the musical similarity based on pitch and timbre features. A. Anglade et al. used the harmony rules that are automatically induced from the music [10]. Low-level features and high-level harmony features were combined to improve genre classification performance. Their final results show that the harmony-based rules contain the useful information for genre recognition. S. Doraisamy et al. used simple feature selection methods for improving genre classification performance [11]. They used correlation-based feature selection (CFS) and chi-square feature evaluation for selecting the informative musical features for Malay traditional genres. Despite its simplicity, their experimental results show that the genre recognition performance can be improved by informative features.

Of the well-known feature selection methods in machine learning community, the min-redundancy and max-relevance (mRMR) is the most widely used method [12]. The proposed method extends mRMR with conditional mutual information for music genre classification. The mRMR incrementally selects a sub of features that minimize the mean of mutual information among a pair of features selected in a subset (i.e., redundancy) and maximize the mean of mutual information among features and label (i.e., relevance). However, the time complexity of mRMR is  $O(N^2)$  as increasing the number of selected features. The efficiency is regarded as its weakness. In this study, the proposed method is designed to improve the time efficiency and the selection performance is reliably maintained.

### III. PROPOSED METHOD

Given a music data set, *N*-dimensional feature vector  $F = \{f_1, ..., f_N\}$  with a target class variable *C*. Feature selection aims to identifying the optimal subset *S* consisted with *n* features, especially  $n \ll N$ . With the optimal subset, classification performance can be improved. In general, the dependency with a feature and class should be maximized. On the other hand, the dependency between a feature and a feature should be minimized.

To this end, the mRMR algorithm optimizes the following

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condition.

$$max_{f_{i} \in F-S_{i-1}} \left[ I(f_{i}; C) - \frac{1}{i-1} \sum_{f_{j} \in S_{i-1}} I(f_{i}; f_{j}) \right]$$
(1)

where  $I(x; y) = \sum \sum p(x, y) \log(p(x, y)/p(x)p(y))$  is a mutual information between x and y; p is a probability density function. The mutual information calculates the dependency of the two variables. The higher value of mutual information means the degree to how much they can describe each other. The dependency with a feature and class is calculated with  $I(f_i; C)$  in (1). The dependency of a feature and a feature is calculated by  $I(f_i; f_j)$  in (1). To satisfy Eq. (1), the mRMR incrementally selects a feature that has the highest dependency to a label (maximal-relevance) and a mutually exclusive feature with already selected features in subset  $S_{i-1}$  with i - 1 features (minimal-redundancy).

However, the objective function is designed to consider both relevance and redundancy at the same time. Except for that the firstly selected feature is considered the dependency with label and the rest features are selected by considering both relevance and redundancy. Therefore, as increasing the number of features in subset, the mRMR tends to consider relevance much less, relative to the previous selection of features. In addition, the time complexity increases to  $O(N^2)$ as the number of calculation for mutual information between feature and feature increases. Therefore, in terms of time efficiency, mRMR has critical disadvantages.

To circumvent this exhaustive repetitive selection, the proposed method is designed to select features using a descending order F counting on the dependency to a target class C. We compute a dependency using mutual information.

$$I(f_i; C) = H(C) - H(C|f_i) = H(C) + H(f_i) - H(f_i, C)$$
(2)

The mutual information between a feature and a label can be represented by the entropy H(T). Here, H(T) measures the uncertainty of a given variable.

$$H(T) = -\sum_{t \in T} p(t) \log p(t)$$
(3)

where p(t) is a probability density function of a random variable t.

After then, the feature vector F is ordered according to its dependency with a target class C. Within the sorted feature vector F, our method selects features that maximize conditional mutual information (CMI) [13].

$$I(f_i; C|S_{i-1}) = H(C|S_{i-1}) - H(C|f_i, S_{i-1})$$
  
=  $H(S_{i-1}, f_i) + H(S_{i-1}, C) - H(S_{i-1}, f_i, C) - H(S_{i-1})$  (4)

The higher value of  $I(f_i; C|S_{i-1})$  means that the  $f_i$  is informative with *C* and less correlated to the previously selected subset  $S_{i-1}$ . Our proposed method selects a feature only when this condition  $I(f_i; C|S_{i-1}) > I(f_{i+1}; C|S_{i-1})$  is satisfied. Under some cases, the algorithm can not identify all of the number of features that should be selected. To address this case, the proposed method employed mRMR to select the rest of features (Step 5 in Algorithm 1). Our proposed method requires a time complexity O(N) when all of the feature set should be identified without mRMR. Therefore, the time efficiency can be achieved compared with the original mRMR selection algorithm. Algorithm 1 shows the steps for selecting n features in a large number of candidate feature set.

Algorithm 1. Proced	ures of Proposed Method
<b>Input :</b> <i>n</i> ;	Number of features to be selected.
<b>Output :</b> <i>S</i> ;	Selected features subset.

Step 1: Initialize  $S \leftarrow \{\emptyset\}$  and  $F \leftarrow \{f_1, \dots f_N\}$ ; For  $\forall x_i \in F$ , calculates I(f; C), and sorts the feature in descending order accordingly, yielding a sorted list of features.

Step 2: Set  $S_1 \leftarrow \{f_1\}$ , and  $i \leftarrow 2$ .

Step 3: If  $I(f_i; C|S_{i-1}) > I(f_{i+1}; C|S_{i-1})$ , then  $S_i \leftarrow \{f_i\}$ 

Step 4: Set  $i \leftarrow i + 1$ , and repeat Step 1-3 until all features in *F* are examined.

Step 5: If necessary, n - |S| are selected by mRMR until n features selected in subset S.

$$\max_{f_i \in F - S_{i-1}} \left[ I(f_i; C) - \frac{1}{i-1} \sum_{f_j \in S_{i-1}} I(f_i; f_j) \right]$$

## IV. EXPERIMENTAL RESULTS

#### A. Genre Data Gathering

In this section, we explain the procedure of collecting the data set for genre classification. We collected representative five genres from the famous online music guide service website called AllMusic.com [14]. We selected 115 songs over five music genres: rap, electronic, jazz, metal and classic. These genres are widely known to people. The segment, extracted from starting 30 seconds, for each song is used for further analysis. For the extraction of musical features, we used MIRtoolbox and JAudio, and compared the performance respectively. Table I represents the detailed information about experimental data set.

#### B. Experimental Setup

To validate the effectiveness of our proposed method, we compare three methods: baseline, baseline using relief, and the proposed method. ReliefF is also the widely-used feature selection method, which requires an input parameter k (the number of nearest neighbors per class); we set this parameter to 1. We identified feature subsets consisted of informative features (from 1 to 50) for dataset. After identifying the feature subset, we applied two classifiers, na we Bayes (NB) and k-nearest neighbor (NN), for genre recognition. Each classification algorithm used the selected 1-50 features for learning. NB classifier creates a recognition model for each five genres. Then this prediction model is used to output the likelihood of each genre for given test data. To calculate the likelihood, we need to preprocess the data. We discretized our dataset using a mean-standard deviation interval scheme. After the preprocessing step, each feature vector is divided into three segments according to  $(-\infty, \mu - \sigma]$ ,  $(\mu - \sigma, \mu + \sigma)$  $\sigma$ ] and  $(\mu + \sigma, +\infty)$  where  $\mu$  is the mean of each feature vector and  $\sigma$  is its standard deviation. The NN classifier calculates all of the Euclidian distances to given samples in the training set, and finds the nearest k samples that have topologically maximum similarity in the Euclidian space. In this test, we set this k parameter to 1, which means that we only consider the most similar sample to classify a genre. Because each feature vector has diverse range values, a feature scaling is required. To adjust feature scales, we used min-max and mean-standard deviation normalizations. We compared the performance of both of the two normalized data sets. To obtain statistically reliable classification results, we conducted a hold-out cross-validation for our experiments. Our dataset is randomly divided into two parts; 80% of the songs are used for learning and the rest 20% of the songs are used for testing the recognition performance. Our experiment was repeated 30 times. We assessed the genre recognition performance with an accuracy measure. Table II represents the detailed information about our experimental setup.

TABLE I: CHARACTERISTICS OF COLLECED	GENRE DATA

Feature extractor	MIRtoolbox	JAudio
# feature	369 916	
# sample	155 songs	
# class	5 genres	
	Genre	# songs
	Rap	30
alass	Electronic	32
class	Jazz	34
	Metal	29
	Classic	30

TABLE II: EXPERIMENTAL SETUP

Classifier	na ïve Bayes	k-nearest neighbor
Data type	continuous	
Discretization	mean-standard	-
Normalization	-	min-max, mean-standard
Input parameter	-	k = 1
Iteration no.		30
Validation	20% hold-out cross-validation	

TABLE III: COMPARISON OF THE PROPOSED METHOD AND CONVENTIONAL METHODS

	reliefF	mRMR	Proposed
MIRtool	0.21	17.23	10.02
Jaudio	0.21	40.99	28.31

#### C. Comparison of Classification Performance

We first investigated the efficiencies of the two feature selection methods. We compared the execution time in seconds for selecting 30 features. Table III indicates that the time cost comparison of conventional methods. The experimental results indicate that our proposed method consumes lower execution time than mRMR. Although the reliefF method finds feature subset faster than other methods, the genre classification performance shows that the feature set selected by reliefF is not useful. Figs. 1-3 show the genre classification results for different classifiers and feature extractors, respectively. The x-axis represents the number of features (10, 20, 30, 40, 50) and the y-axis represents the classification accuracy.

Fig. 1 shows the genre classification accuracy using NB classifier. The base line (gray line) in Fig. 1(a) indicates the result of using all of the features for learning. From the results, it is observed that some irrelevant features are included in a large number of musical features. These irrelevant features degrade the genre recognition performance. Our proposed method is able to filter those irrelevant features and selects

useful musical features that in much informative to genre classification. We see that the proposed method improved the classification performance from 45% (baseline) to 64%. Even though the reliefF+NB showed worse accuracy than the proposed method did, it yielded better results than the baseline in most cases. Fig. 1(b) shows the classification result for a dataset using MIRtoolbox features. Although our result reports the lower recognition performance than the base line that uses 369 full features, we found that our method gives a similar classification accuracy when the size of feature subset reaches 50.



(b) Accuracy for a dataset with MIRtoolbox features Fig. 1. Comparison of classification accuracy for baseline+NB, reliefF+NB, and the proposed+NB for two data sets.



(b) Accuracy for a dataset with MIRtoolbox features Fig. 2. Comparison of classification accuracy for baseline+NN, reliefF+NN, and the proposed+NN for two data sets. (min-max normalized).

Fig. 2 shows the genre classification accuracy using NN classifier for two normalized data sets. Our result shows the improvement of classification performance, regardless of feature sets. Especially on MIRtoolbox feature set, the proposed method achieved over 20% improvement against

the baseline+NN. The accuracy of the reliefF+NN method is often lower than that of baseline+NN, whereas the proposed method showed reliable improvement in all cases.



(b) Accuracy for a dataset with MIRtoolbox features Fig. 3. Comparison of classification accuracy for baseline+NN, reliefF+NN, and the proposed+NN for two data sets (mean-standard normalized).

_	С	М	J	Ε	R
R	1	4	8	14	21
Е	1	1	2	8	2
J	1	0	16	4	4
м	4	22	1	2	2
С	23	2	7	4	1
(a) confusion matrix of ReliefF+NN					
	С	М	J	Е	R
R	0	1	1	7	22
Е	0	0	2	16	4
J	2	2	25	4	3
М	0	26	2	2	1
с	28	0	4	3	0

(b) confusion matrix of the proposed method+NN Fig. 4. Confusion matrix of reliefF+NN and the proposed+NN using MIRtoolbox features.

Fig. 3 shows the genre classification accuracy using NN classifier for two mean-standard normalized data sets. The genre classification performance is found to be improved when the proposed feature selection method is combined with NN classifier. We observe that the proposed method provides reliable accuracies regardless of normalization schemes. It is noteworthy that the highest performance is yielded when combined with mean-standard deviation

normalization. Fig. 4 shows the confusion matrices of genre recognition for the reliefF+NN and the proposed+NN; the features are extracted by MIRtoolbox. Due to the space limitation, each genre is represented with a capital; R(rap), E(electronic), J(jazz), M(metal) and C(classic). The rows and columns of each matrix represent actual genre of input songs and their predicted genre that is classified by NN, respectively. Fig. 4(a) is the confusion matrix of the reliefF+NN method. Fig. 4(b) shows the confusion matrix of the proposed+NN. We can see from the confusion matrices that the proposed method is more effective for the classification of electronic and jazz genres than the reliefF+NN method. Compared with the reliefF+NN, genre is represented with a capital; R(rap), E(electronic), J(jazz), M(metal) and C(classic). The rows and columns of each matrix represent actual genre of input songs and their predicted genre that is classified by NN, respectively. Fig. 4(a) is the confusion matrix of the reliefF+NN method. Fig. 4(b) shows the confusion matrix of the proposed+NN. We can see from the confusion matrices that the proposed method is more effective for the classification of electronic and jazz genres than the reliefF+NN method. Compared with the reliefF+NN, the accuracy of the proposed method is improved from 58.06% to 75.48%.

# V. CONCLUSION

In this paper, we presented a feature selection algorithm for improving the genre classification. Through the experimental results, we note that our method is able to identify the genre-discriminative musical features. In comparison of other traditional method, the proposed method gives an effective performance for further improvement. We also found that with the only 50 musical features, a classification algorithm is able to learn the inherent rules between musical features and genres considerably well.

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