

A New Genre Classification with the Colors of Music

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Abstract

The aim of this study is to bring a new perspective for the classification of the songs, revealing of the colors of music. The first effort is to transform songs into images. The colorful images have been attained with Short time Fourier transform, discrete cosine transform and time to spatial transformation and some extra processing. It has been observed that the images of different music genres obtained with the same method have different colors. But some of them have similar colors and patterns, which making difficult to classify. Pre-trained deep convolutional network have been trained with these images. For five Turkish musical genres, nearly up to 60% classification accuracy has been achieved and for ten musical genre of a benchmark musical dataset nearly up to 54% classification accuracy has been achieved. In future studies, it has been planned to create the images using timbral texture and rhythmic contents, for increasing the accuracy.

Keywords: Convolutional neural networks, music genre classification, discrete cosine transfo

Müzik Türlerinin Derin Öğrenme Ağları ile Sınıflandırılması

Öz

Bu çalışmada günümüzde görüntülerin sınıflandırılmasında yüksek başarı sağlayan derin öğrenme ağları ile müzik türlerinin sınıflandırılması hedeflenmiştir. Bu çalışmanın amacı, müziklerin renklerini ortaya çıkararak şarkıların sınıflandırılması için yeni bir bakış açısı getirmektir. Bu amaçla ilk olarak, müzik türlerinden seçilen parçalar görüntülere dönüştürülmüştür. Renkli görüntüler kısa zaman fourier dönüşümü, ayrık kosinüs dönüşümü ve uzamsal dönüşüm yöntemleri ve bazı önışlemlerle elde edilmiştir. Farklı türlere ait görüntülerin renklerinin farklı olduğu görülmüştür. Ancak bazı türlerde sınıflandırmayı zorlaştıracak benzer renkler ve desenler görülmüştür. Önceden eğitilmiş derin konvolüsyon ağı bu görüntülerle eğitilmiştir. Türkçe müziklerden seçilen, arabesk, pop, türk halk müziği, türk sanat müziği ve rock müzikleri ile eğitilen ağda, yaklaşık % 60'a kadar bir sınıflandırma doğruluğu elde edilmiş ve yine literatürde müzik türü sınıflandırılmasında kullanılan genel bir veri tabanı ile yapılan testlerde, on farklı müzik türü için yaklaşık% 54'e kadar bir sınıflandırma doğruluğu elde edilmiştir.

Anahtar Kelimeler: Müzik Türlerinin Sınıflandırılması,Derin Öğrenme,Ayrık Kosinus Dönüşümü, Hızlı Fourier Dönüşümü,Kısa Zamanlı Fourier Dönüşümü

1. Introduction

With the development of computer based systems, the number of files has increased since a lot of documents, music files, image files were created easily.

So many documents have also been creating messy folders. One way to alleviate the problem is to manage the files automatically. After automatic classification of files, files are distributed to the folders storing related files. Automatic classification of files requires intelligent systems, which

understand the content of the files. Genre classification of audio data [1], paintings [2], web pages [3] and music [4] are some of the studies.

Music genre is a label defined by human categorizing the music. With these labels, music or songs are classified either manually or automatically. But it is a fact that there is not strict definition among genres [5, 6].

Since 1990's, with the increasing abilities of microprocessors for multi-media, genre classification of music has been started to have been studied. In some of the first studies, a genre classification system for TV sound signals, genre identification for videos and TV program genre classifications [7,8,9] have been realized using spectrogram analysis, audio pattern extraction and distinctive cinematic aspects respectively.

The next studies have been focused on musical genre classification, music information retrievals, music annotation and indexing [10].

Today, there are a lot of applications presented in the virtual markets. These applications offer individual playlists making genre classification. Several methods have been used for genre classification. As most of the studies based on genre classification, there are two main efforts. Firstly features, abstracting the real large data with few parameters have been selected. Secondly a good classifier for features has been selected discriminating the genres. Three sets of features for presenting timbral texture, rhythmic content and pitch content are proposed [5]. Statistical pattern recognition methods such as Gaussian classifier and K-nearest neighbor have been selected for classification in this study. In another study, the pitch contour of the song refrain, the pitch contour of all the song notes and the duration contour of all the song notes have been selected [11] and neural networks have been used for classification. In [12] Beat spectrum, LPC (linear predictive coding), zero crossing rates, spectrum power and mel frequency cepstral coefficients have been used as features and musical genres have been classified with support vector machines. In [13], linear discriminant analysis (LDA) and support vector machines used for classification of genres using the same features in [5]. Music genre classification using data mining algorithm [14] and Gaussian mixture model [15] have also been used. In recent years, the new classifiers have also been used for musical genre classification. Deep convolutional neural networks (CNN) have been used for the classification of musical genres [20, 21].

2. Genre Classification Process

In this study, it has been aimed to present the features of music as visually. In the literature there are quite a lot of studies trying to find which features presents the musical genre best. But there is no study looking these features as an image. There is only one latest study using spectrogram images for speech music discrimination with deep convolutional networks [25]. So according to our research, this study is the first effort using STFT, DCT and time to spatial transformation as image for genre classification. With this aim, GTZAN dataset [5] has been used [24] for musical genre classifications. And a new dataset containing five Turkish musical genres has been prepared for this study. The whole part of the music data have been used for conversion.

2.1 Transforming Music In to Images

In this process, four different methods have been used for transformation. In the first method, Short Time Fourier Transform coefficients has been transformed into proper $m \times m \times 3$ matrix, normalized the values, resized to $227 \times 227 \times 3$ images and saved.

In the second method and third methods discrete cosine transform (DCT) have been used. In the second method, a fixed number of DCT ($1024 \times 1024 \times 3$) coefficients have been taken and transformed to the matrix, normalized and resized to $227 \times 227 \times 3$. In the third method a floating number of DCT coefficients have been taken, which summarizes the data best. Lastly only musical data have been transformed to the images.

Arabesque, Turkish Folk Music, Pop Music, Rock Music and Turkish classic music songs have been selected. Transformation process for DCT has been given in Figure 1.

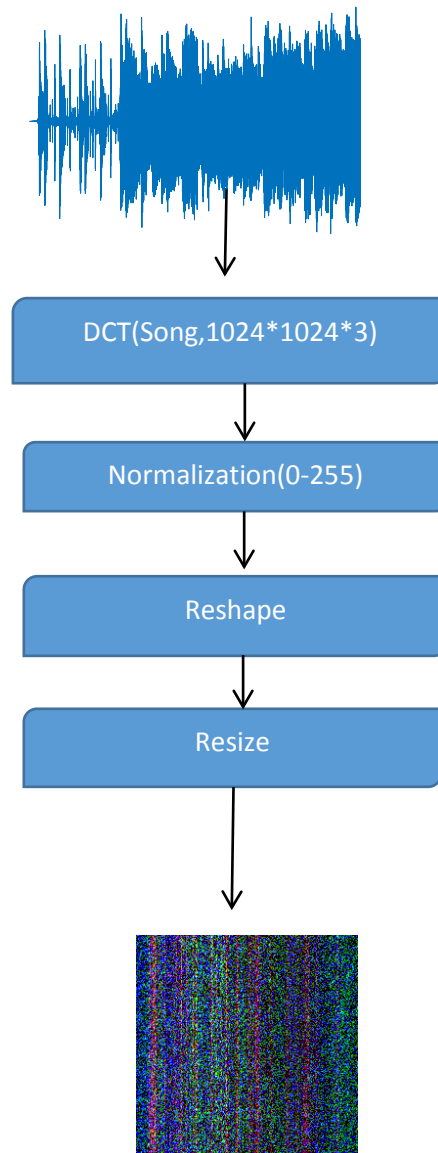


Figure 1. Music to Image transformation with DCT

In each process, different main colors have been attained for each genre. Table 1 shows sample images (belong to the same song) attained with four methods.

2.2 Training And Testing The Classification Accuracy Of Images

In the first test in our study, 150 music images for each genre have been used for training and testing. The 70% and 80% of examples have been used for training and 30 % and 20% of examples have been used for testing respectively.

For the classification of the musical genres, using these images, pre-trained deep convolutional neural network(AlexNET) has been trained and tested using Matlab© 2018 Deep Learning Toolbox. AlexNET has a CNN structure designed by Alex Krizhevsky, Geoffrey Hinton, and Ilya Sutskever[26]. It has been used 25 layered default network structure in the study. 227X227X3 inputs and 5 outputs for Turkish Musical Classification and 10 outputs for GTZAN have been used. The net contains convolutions, max pooling, ReLU and fully-connected layer. The classification system has been given in Figure2

The results have been submitted in Table 2. Since the execution time of these methods is not comparable with the other studies, it has been omitted for this study.

Table 1. The colors of Turkish Music for Each Genre

Musical Genre	Applied Method			
	STFT	DCT Fixed	DCT Float	Time to Spatial
Arabesque				
Turkish Pop				
Turkish Rock				
Turkish Classical				
Turkish Folk				

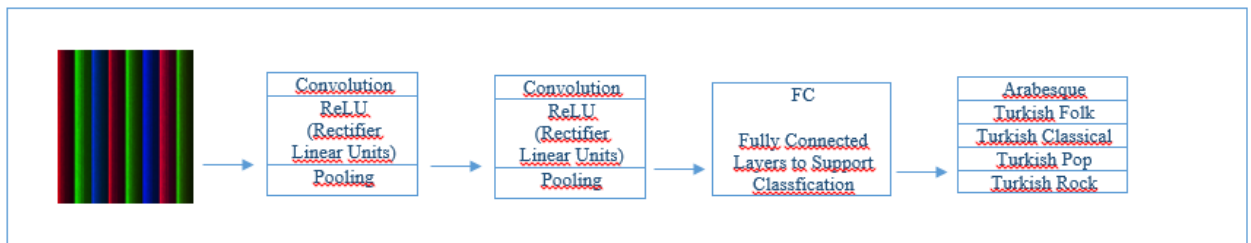


Figure 2. Genre Classification System

Table 2. Classification accuracy of Turkish music dataset

METHOD	ACCURACY ACCORDING TO TRAINING DATA PERCENTAGE	
	70%	80%
TIME TO SPATIAL	0.4209	0.4467
FIXED DCT	0.6061	0.5736
FLOATING DCT	0.4747	0.4619
STFT	0.5503	0.5404

In order to validate the classification success of the transformed images, GTZAN dataset has also been used. In this dataset, ten genres and 1000 music data have been used for classification. 100 music images for each genre have been used for training and testing. The images belong to these genres have been given in Table 3. The 70% and 80% of examples have been used for training and 30 % and 20% of examples have been used for testing respectively. The classification results have been submitted in Table 4.

Table 3. The colors of GTZAN database for each genre

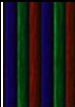
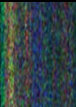
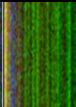
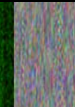
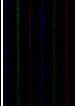
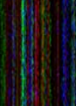

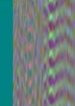

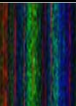
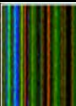

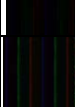
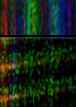
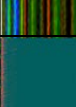
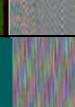
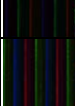
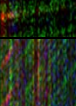
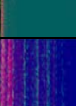
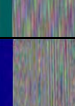
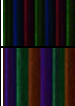
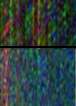
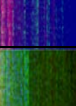
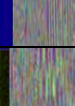
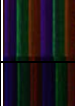
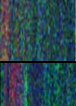
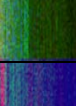
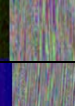
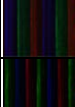
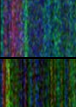
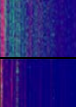
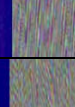
Musical Genre	Applied Method			
	STFT	DCT Fixed	DCT Float	Time to Spatial
Blues(77)				
Country(30)				
Classical(89)				
Hiphop(87)				
Pop(65)				
Metal(52)				
Rock(40)				
Jazz(54)				

Table 3. The colors of GTZAN database for each genre (Continue)

Musical Genre	Applied Method			
	STFT	DCT Fixed	DCT Float	Time to Spatial
Disco(67)				
Reggae(77)				

Table 4. Classification accuracy of GTZAN dataset

METHOD	ACCURACY ACCORDING TO TRAINING DATA PERCENTAGE	
	70%	80%
TIME TO SPATIAL	0.3600	0.3650
FIXED DCT	0.3733	0.3950
FLOATING DCT	0.3733	0.3700
STFT	0.5433	0.5350

3. Conclusion

In this study, the first and foremost aim is to convert musical data to images. The idea behind these efforts is that “The harmony in the music gives us a visual harmony.” Another reason for us to convert musical data to the images is that we wanted to use the power of the AlexNet pre-trained network which was trained more than one million images. According to the 1750 images attained with the transformations, results verify this idea. Another idea is that “The images of music data can also discriminate the different genres”. The results are promising. The figures can be used for online musical applications. In future studies, we are planning to design a musical genre classification system.

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