

FAST SOUND FILE CHARACTERISATION METHOD

Lucille Tanquerel and Luigi Lancieri
France Télécom R&D, 42 rue des coutures, Caen, France

Keywords: Musical similarities, rhythm, variation.

Abstract: This article describes a fast technique of characterization of sound documents based on a statistical measure of the variation of the signal. We showed that a very limited sampling was sufficient to obtain a reasonable performance of the characteristic while being 100 times faster to calculate than a complete sampling. During preliminary tests, we carried out a first validation of our approach by highlighting a correlation of 0.7 between the human perception of the rhythm and our characteristic as well as an error of recognition lower than 5%. In this new series of tests, we show that our approach makes possible to associate to a cut file its missing half, with an error rate from approximately 30%.

1 INTRODUCTION

Many sources give a report of needs and strong commercial potential related to the automated management of sound documents.

The description of the sound characteristics is a key element to carry out automatic treatments of audio data. This type of measurement can be useful not only to characterize the data but also to describe the musical tastes of the users on the basis of their activity of listening. These techniques become critical taking into account the increasing quantity of sound documents found on the Web or in content providers musical data bases. Many works were completed in this field but the techniques of treatment remain heavy to implement and are missing standards.

The objective of this document is to describe a method making it possible to generate compactly and rapidly a signature of a sound file by the extraction of physical characteristics distributed on the file. The innovation of our proposal relates on the organization of the extraction of the samples and on the mode of analysis to provide very quickly a representative signature of the musical content.

The organization of the extraction defines the way the samples are taken. It is possible, for example, to determine the spectrum on the whole musical file or only over the first minute. Our proposal aims at carrying out a minimal sequential statistical sampling distributed on the sound file according to a particular law of probability.

The first work described in (Tanquerel, 2006) showed on the one hand the stability of the signature in spite of a random and limited sampling. In addition, this work showed that the signature offered a good representativeness of the rhythmic nature of the musical contents. In this work, we wished to go further concerning the capacity of discrimination of the signature, the objective being to cut a file in two equal parts in order to see whether the comparison between the signatures of each half makes it possible to determine if these two halves are those of the same file.

2 GENERAL DESCRIPTION

The following figure shows the bases of the signature process from the analysis of samples taken from a sound file. The idea is to capture the image of the swinging of the sound spectrum such as we can perceive it while observing bars-graph of an audio reader. The samples to be analyzed are collected by triplets (E0, E1, etc.) of contiguous specimen of duration K. In this study, each triplet is collected in a random way but by respecting a chronological order. I.e. if one decides to take 10 triplets, the only constraint will be that the first one precedes the second one which will have to precede the third one, etc. The space of time between each triplet could be unspecified and the sum of all triplets will cover a limited part of the file.

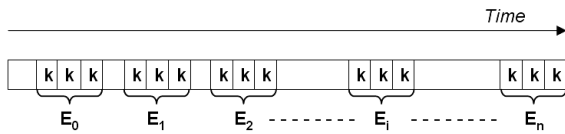


Figure 1: Collect of samples by triplet in a sound file.

On each sample k of each triplet, we compute the distribution of frequencies within the meaning of Fourier and the directing coefficient p of the straight regression line binding the level (y) to each class of the spectrum frequency (x). This straight regression line is expressed in the following way: $y = px + b$.

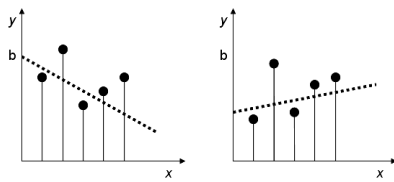


Figure 2: The slope of the spectrum of 2 elements of a triplet.

The analysis of the behaviour of p (slope of the line side of figure 2) will contribute to evaluate the rhythmic behaviour by measuring the swinging of the spectrum over one period, and in average value on the various samples. By reference to mechanics, this swinging, its speed and its acceleration are evaluated as follows.

The first stage consists in identifying the number of triplets as well as their position in the signal. On a fraction of the sound file, we extract the first triplet on which we calculate the 3 spectra then the directing coefficients of the straight regression lines. Thus 3 values of slope (p_{11} , p_{12} , p_{13}) are obtained. The speed of swinging is obtained by calculating the difference between 2 consecutive slopes. We obtain 2 values of speed (v_{11} , v_{12}) for each triplet. Acceleration a_1 , single by triplet, is evaluated on speeds variation. We recompute these data on the following triplet and so on until the end of the file. At the end of the operation we have a set of values of coefficients [$(p_{11}$, p_{12} , $p_{13})$, $(p_{21}$, p_{22} , $p_{23})$, ..., $(p_{n1}$, p_{n2} , $p_{n3})$], speeds [$(v_{11}$, $v_{12})$, $(v_{21}$, $v_{21})$, ..., $(v_{n1}$, $v_{n2})$] and accelerations (a_1 , a_2 , ..., a_n) for n triplets representative of the piece of music. The behaviour of swinging (position, speed and acceleration) is obtained by a combination of the average values and standard deviation of all these data (p_i , v_i , a_i).

The analysis of the behaviour of p (slope of the line side of figure 2) will contribute to evaluate the rhythmic behaviour by measuring the swinging of

the spectrum over one period, and in average value on the various samples. By reference to mechanics, this swinging, its speed and its acceleration are evaluated as follows.

The first stage consists in identifying the number of triplets as well as their position in the signal. On a fraction of the sound file, we extract the first triplet on which we calculate the 3 spectra then the directing coefficients of the straight regression lines. Thus 3 values of slope (p_{11} , p_{12} , p_{13}) are obtained. The speed of swinging is obtained by calculating the difference between 2 consecutive slopes. We obtain 2 values of speed (v_{11} , v_{12}) for each triplet. Acceleration a_1 , single by triplet, is evaluated on speeds variation. We recompute these data on the following triplet and so on until the end of the file. At the end of the operation we have a set of values of coefficients [$(p_{11}$, p_{12} , $p_{13})$, $(p_{21}$, p_{22} , $p_{23})$, ..., $(p_{n1}$, p_{n2} , $p_{n3})$], speeds [$(v_{11}$, $v_{12})$, $(v_{21}$, $v_{21})$, ..., $(v_{n1}$, $v_{n2})$] and accelerations (a_1 , a_2 , ..., a_n) for n triplets representative of the piece of music. The behaviour of swinging (position, speed and acceleration) is obtained by a combination of the average values and standard deviation of all these data (p_i , v_i , a_i).

3 STATE OF THE ART

The process described in this document is distinguishable from former work by a better descriptive capacity compared to resources necessary for calculation and storage. The descriptive capacity is related to the rhythmic evaluation by the analysis of the swinging structure. These elements do not need to be obtained on the whole sound file; a limited statistical sampling is enough. The signature requires a priori only the storage of a very limited quantity of numerical data. In addition, the signature will be almost independent of the format or the sound quality of the piece, even if this last one is incomplete.

The existing techniques for the characterization of musical files and research of similarities (MIR - Music Information Retrieval) are various. There are three principal approaches: those based on signal processing, collaborative filtering, and data mining. The approaches based on signal processing consist in analyzing directly the content of the audio file (signal and spectrum). In general, these characteristics are modelled by learning systems, and comparisons are carried out for the research of similarities (McKay, 2004, Tzanetakis, 2001). Another example of technology as regards acoustic

prints is the TRM (This Recognizes Music) (<http://rm.relatable.com>). This technology was developed by the American company Relatable. Basically, this system allows the recognition of pieces of music by acoustic analogy exploiting “audio code bar” type of print which generates a single signature. As soon as the numerical print was created, it is sent to the TRM server, which compares the print with that of an existing song in the data base of a customer. The last commercial version of TRM server can manage more than 5000 prints (already extracted) per second, or until several billion requests per day.

4 PERFORMANCES

To evaluate the performances of our method we carried out a series of preliminary works which showed a certain level of representativeness of our numerical signature, in particular compared to the human perception of the rhythm. Indeed by questioning a group of 10 users so as to evaluate their perception of the rhythm on 2 corpora respectively composed of 28 and 50 pieces of music. The first corpus was made up so as to represent a broad rhythmic spectrum; the second corpus was made up of audio pieces chosen randomly. The results showed a level of correlation between the signature and the opinions of the users of about 0.7. In a second experiment we sought to evaluate the validity of the signature in the case of several sequential samplings of a same piece. This validation is particularly important taking into account the very low level of coverage of about 5 to 10% for each audio piece. There still, the results are rather encouraging because the results of 50 successive signatures are homogeneous in more than 93% of the cases. The reader can refer to this work (Tanquerel, 2005) for more details.

We present in the continuation of this document a series of more recent works aiming at confirming the reliability of our signature under a complementary point of view. In this case, we constituted a corpus of 100 pieces so as to cover various musical kinds.

4.1 Principle of the Validation Method

In this new series of tests, each file is cut out in two equal parts. The goal is to compare all the halves between each other in order to see whether the signature similarity makes it possible to associate to each half its missing half. Considering the limited

sample size and the limited rate of covering, the probability of sampling parts musically similar in each half of the same piece is very weak. Under these conditions, we consider that the capacity of recognizing automatically the two parts of the same audio piece is a good indication of the descriptive capacity of the signature.

In our approach, we consider that two halves are associated when the difference (in absolute value) of their signature is lower than a certain threshold.

For n audio pieces, we will have two sets of halves ($m1a, m2a, m3a... mna$) and ($m1b, m2b, m3b... mnb$) both of cardinal n . Each $m1a, i = \{1... n\}$ is compared with each $m1b, j = \{1... n\}$.

The results are expressed with percentages: percentage of recognized exact associations (%rec), percentage of association errors (%err), and percentage of dissociation errors (%diss).

4.2 The Tests

For these tests, we used the whole of 100 pieces describes higher. The principle is to increment the value of the threshold until the percentage of recognitions reaches the 100% (which has as a consequence a null percentage of dissociation errors) The characteristic of the signature taken into account is speeds standard deviation (SSD) or accelerations standard deviation (ASD): the rate of covering is 20% and then 25%, the sample size is 1024, 2048, 4096 and then 8192

Then the goal is to find the optimum. This one is not inevitably reached for a maximum rate of recognitions because a maximum rate of recognitions can be combined at a very important association error rate.

4.3 Calculation of the Optimum

The concept of optimum is often complex and difficult to evaluate. This study does not escape the rule. We thus make two proposals to evaluate the optimum in our measurements.

First proposal: the optimum is reached when at least 50% of the pieces were recognized and when the association error rate is lower than 33%.

Here are some results in the following tables. Each table is divided into two distinct parts, corresponding to the two different rates of covering (20% and 25%). The columns %rec and %err respectively represent the percentage of recognitions and the percentage of association errors.

In each box, we can read the value of the fork in which the optimum is. The best results are indicated in bold.

S S D	20%			25%		
	%rec	%err	threshold	%rec	%err	threshold
10	50	22,77	105	50	21,17	98
24	61	32,94	155	69	32,02	150
20	50	24,04	97	50	21,68	87
48	63	32,74	134	70	32,85	133
40	50	26,2	83	50	20,95	66
96	58	32,97	106	68	32,67	104
81	50	21,13	43	50	20,36	42
92	64	32,95	69	70	32,56	67

Figure 3: Results for SSD.

The results for ASD do not appear there but they are likely the same as SSD. The optimal results are located in the same boxes for each table (8192 - 20% or 8192 - 25%). Contrary to what our first work had us think, a minimal sampling, as well on the level of the rate of covering as of the sample size, seems not being really interesting.

Second proposal: we look at which place the crossing between the curve of association errors and the curve of dissociation errors is located. The principle is the same as that is described here in former work concerning the robustness of the signature.

The results are presented with this table (ASD only).

ASD	20%			25%		
	% err	% diss	threshold	% err	% diss	threshold
1024	35,91	35	242	32,13	32	213
2048	35,49	35	213	31,25	31	193
4096	37,87	37	205	32,07	32	106
8192	34,48	35	129	30,15	29	109

Figure 4: Results for ASD.

Likewise the results concerning the first proposal, the optimal values are in the boxes 8192 - 20% or 8192 - 25%.

It is noted that the percentage of errors (association and dissociation) reaches an average value of 30%, which implies a percentage of recognitions of 70%. This value is high considering that the analysed parts of the audio piece are in fact

different. This shows that our method has a good capacity of intrinsic recognition.

The results of these last tests are rather promising and it could be interesting in later work to combine variously the characteristics SSD and ASD in order to see whether we can increase the performances of our method.

5 CONCLUSION

The characterization of the musical files represents an important stake insofar as it makes it possible to consider the indexing and the automated and powerful management of multimedia contents. This automation can be applied of several ways implying the sound document itself or the user from the point of view of modelling musical perception.

In this context, we developed and patented a fast technique of characterization based the variation of the signal. We showed that a limited sampling of sequences was sufficient to obtain a reasonable performance of the characteristic while being more than 100 times faster to calculate than a complete sampling. We approached the methodology of validation according to two different angles: the matrix of confusion and the comparison with human perception. Each one of these methods makes it possible to conclude that the technique offers a coherent and more than all a fast representation of the sound files.

This work opens other prospects to us, in particular in the combination of the various characteristics.

REFERENCES

- Tanquerel, L., Lancieri, L., 2005. Mesure rapide de similarités musicales – Perception du rythme. CORESA 2006
- McKay, C., Fujinaga, I., 2004. Automatic genre classification using large high-level musical. ISMIR 2004.
- Tzanetakis, G., Essl, G., Cook, P., 2001. Automatic musical genre classification of audio signals. ISMIR 2001