Chord Recognition by Fitting Rescaled Chroma Vectors to Chord Templates

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***Abstract*—In this paper, we propose a simple and fast method for chord recognition in music signals. We extract a chromagram from the signal which transcribes the harmonic content of the piece over time. We introduce a set of chord templates taking into account one or more harmonics of the pitch notes of the chord and calculate a scale parameter to fit the chromagram frames to these chords templates. Several chord types (major, minor, dominant seventh, etc.) are considered. The detected chord over a frame is the one minimizing a measure of fit between the rescaled chroma vector and the chord templates. Several popular distances and divergences from the signal processing or probability fields are considered for our task. Our system is improved by some post-processing filtering that modifies the recognition criteria so as to favor time-persistence. The transcription tool is evaluated on three corpora: the Beatles corpus used for MIREX 08, a 20-audio-song corpus, and a resynthesized MIDI corpus. Our system is also compared to state-of-the-art chord recognition methods. Experimental results show that our method compares favorably to the state-of-the-art and is less computationally demanding than the other evaluated systems. Our systems entered the MIREX 2009 competition and performed very well.**

***Index Terms*—Chord recognition, music information retrieval, music signal processing, music signal representation.**

I. Introduction

COMPLETE musical analysis of a pop song, that is to say the transcription of every single note played by every instrument is a very complex task. The musical content of a pop song is thus more often translated into a more compact form such as sequences of chords. A chord is a set of notes played simultaneously. A chord can be defined by a *root note* which is the note upon which the chord is perceived and a *type* giving the harmonic structure of the chord. For example a *C major* chord is defined by a root note *C* and a type *major* which indicates that the chord will also contain the major third and the perfect fifth, namely the notes *E* and *G*. The result of chord transcription consists in sequences of chords played successively with their respective lengths. This compact and robust writing not only helps to play-back the song but also gives information on the harmonic content and structure of the song. Automatic chord transcription finds many applications in the field of Musical Information Retrieval. The characterization of a song by its chord transcription can be used in several tasks among which song identification, query by similarity, or analysis of the structure of the piece.

Automatic chord transcription includes in most cases two successive steps: a feature extraction which captures the musical information and a recognition process which outputs chord labels from the extracted features.

The first step consists in the extraction of relevant and exploitable musical content from the audio. As such, pitch perception of a note can be decomposed into two different notions: *height*, corresponding to the octave to which the note belongs and *chroma* or *pitch class* indicating the relation of the note with the other notes among an octave. For example the note *A4* (440 Hz) is decomposed into an octave number *4* and a chroma *A*. The features used in chord transcription may differ from a method to another but are in most cases variants of the *Pitch Class Profiles* introduced by Fujishima [1] whose calculation is based on this notion of chroma. These features, also called *chroma vectors*, are 12-dimensional vectors. Every component represents the spectral energy of a semi-tone on the chromatic scale regardless of the octave. These features are widely used both in chord recognition and tonality extraction. The calculation is based either on the *constant Q transform (CQT)* [2] or on the *short-time Fourier transform (STFT)* and is performed either on fixed-length frames or variable-length frames (depending for example on the tempo, etc.). The succession of these chroma vectors over time is often called *chromagram* and gives a good representation of the musical content of a piece.

The structure of a chord being entirely defined by its root note and type, it is easy to create 12-dimensional chord templates which reflect this structure by giving a particular amplitude to every chroma. The simplest model for chords, widely used in chord recognition [1], [3], has a binary structure giving an amplitude of 1 to the chromas constituting the chord and 0 for the other chromas. Other models can be introduced for example by taking into account the harmonics of the notes played in the chord [4], [5].

The present paper focuses mainly on the second part of the chord transcription process that is to say the chord labeling of every chromagram frame. Our chord recognition system is based on the intuitive idea that for a given 12-dimensional chroma vector, the amplitudes of the chromas present in the chord played should be larger than the ones of the non-played chromas. By introducing chord templates for different chord types and roots, the chord present on a frame should therefore be the one whose template is the *closest* to the chroma vector

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according to a specific measure of fit. A scale parameter is introduced in order to account for amplitude variations and finally the detected chord is the one minimizing the measure of fit between the rescaled chroma vector and the chord templates.

Section II provides a review of the state-of-the-art methods for the chord recognition. Section III gives a description of our recognition system: the chord templates, the measures of fit and some post-processing filtering methods exploiting time-persistence. Section IV describes the evaluation protocol for our method. Section V presents a qualitative and quantitative analysis of the results on a data corpus formed by the 13 Beatles albums and a comparison with the state-of-the-art. Section VI gives results on another corpus composed of audio files synthesized from MIDI and investigates the influence of the genre, percussive noise, and beat-synchronous chord detection.

II. State of the Art

The chord recognition task consists in outputting a chord label from a specific music-related feature. Most chord recognition systems use a chromagram (or assimilate) as an input to the system and output a chord label for each chromagram frame. Machine-learning methods such as hidden Markov models (HMMs) have been widely used for this task especially in the last years but templates-fitting techniques have also been used for this labeling process.

A hidden Markov model is constituted by a number of hidden states with an initial state distribution, a state transition probability distribution which gives the probability of switching from a state to another and an observation probability distribution which gives the likelihood of a particular state for a particular observation data. In the typical HMM-based chord recognition systems every chord is represented by a hidden state and the observations are the chromagram frames. Given the parameters of the model, the chord recognition consists in finding the most likely sequence of hidden states (chords) that could have generated a given output sequence (chromagram). The parameters of these HMMs (initial state distribution, state transition probability distribution and observation probability distributions) are either based on musical theory, learned on real data, or a combination of these two approaches.

The first HMM used in chord recognition [6] is composed of 147 hidden states each representing a chord and corresponding to seven types of chords (major, minor, dominant seventh, major seventh, minor seventh, augmented, and diminished) and 21 root notes (12 semi-tones with the distinction between $\flat$ and $\sharp$). All the HMM parameters are learned by a semi-supervised training with an EM algorithm. This model is then improved in [7] by a complete re-building of the HMM. The number of hidden states is reduced from 147 to 24 by only considering major and minor chords; this enables to have sufficient data for the training process. The initializations for the HMMs parameters are inspired by musical and cognitive theory which naturally introduced musical knowledge into the model. The state transition probability distribution and the initial state distribution are still updated by an unsupervised training with an EM algorithm but the observation probability distributions are fixed, giving to each chord a clear and predetermined structure. The introduction of tempo-based features also enhances the recognition performances. Some other methods [5], [8] also use a 24-state HMM considering only major and minor chords but try different sets of input features, HMM parameters or training approaches. Symbolic data can be used for the training process with a system based on 24 tonality-dependent HMMs [9] in order to give a joint key extraction and chord transcription.

Yet, the first chord recognition system based on chroma representation proposed by Fujishima [1] is not using HMM but chord dictionaries composed of 12-dimensional templates constituted by 1 (for the chromas present in the chord) and 0 (for the other chromas). 27 types of chords are tested and the transcription is done either by minimizing the Euclidean distance between *pitch class profiles* and chord templates or by maximizing a weighted dot product. Fujishima's system is improved [3] by calculating a more elaborate chromagram including notably a tuning algorithm and by reducing the number of chords types from 27 to 4 (major, minor, augmented, diminished). Chord transcription is then realized by retaining the chord with higher dot product between the chord templates and the chromagram frames. Chord transcription can also be done by maximizing the correlation between enhanced variants of the *pitch class profiles* and chord templates [10]. These chord templates are also used on MIDI data for the joint tasks of segmentation and chord recognition [11] by the calculation of weights reflecting the similarity between the chord models and the present notes in a segment.

III. Our System

A. General Idea

Let $\mathbf{C}$ denote the chromagram, with dimensions $M \times N$ (in practice $M = 12$) composed of N successive chroma vectors $\mathbf{c}_n$. Let $\mathbf{p}_k$ be the 12-dimensional chord template defining chord k. We want to find the chord k whose template $\mathbf{p}_k$ is the *closest* to the chromagram frame $\mathbf{c}_n$ for a specific measure of fit. We propose to measure the fit of chroma vector $\mathbf{c}_n$ to template $\mathbf{p}_k$ up to a scale parameter $h_{k,n}$. Given a measure $D(.;.)$, a chroma vector $\mathbf{c}_n$, and a chord template $\mathbf{p}_k$, the scale parameter $h_{k,n}$ is calculated analytically to minimize the measure between $h\mathbf{c}_n$ and $\mathbf{p}_k$

$$h_{k,n} = \arg\min_h D(h\mathbf{c}_n; \mathbf{p}_k). \tag{1}$$

In practice $h_{k,n}$ is calculated such that

$$\left[\frac{dD(h\mathbf{c}_n; \mathbf{p}_k)}{dh}\right]_{h=h_{k,n}} = 0. \tag{2}$$

We then define $d_{k,n}$ as

$$d_{k,n} = D\left(h_{k,n}\mathbf{c}_n; \mathbf{p}_k\right). \tag{3}$$

The detected chord $\hat{k}_n$ for frame n is then the one minimizing the set $\{d_{k,n}\}_k$

$$\hat{k}_n = \arg\min_k d_{k,n}. \tag{4}$$

TABLE I
PRESENTATION OF THE MEASURES OF FIT (THE EXPRESSIONS ASSUME $\|\mathbf{p}_k\|_1 = 1$)

	Expression of $D\left(h_{k,n}\,\mathbf{c}_n;\mathbf{p}_k\right)$	Scale parameter $h_{k,n}$	Minimization criteria $d_{k,n}$
EUC	$\sqrt{\sum_m \left(h_{k,n}\,c_{m,n} - p_{m,k}\right)^2}$	$\frac{\sum_m c_{m,n}\,p_{m,k}}{\sum_m c_{m,n}^2}$	$\sqrt{\sum_m p_{m,k}^2 - \frac{\left(\sum_m c_{m,n}\,p_{m,k}\right)^2}{\sum_m c_{m,n}^2}}$
IS1	$\sum_m \frac{h_{k,n}\,c_{m,n}}{p_{m,k}} - \log\left(\frac{h_{k,n}\,c_{m,n}}{p_{m,k}}\right) - 1$	$\frac{M}{\sum_m \frac{c_{m,n}}{p_{m,k}}}$	$M\log\left(\frac{1}{M}\sum_m \frac{c_{m,n}}{p_{m,k}}\right) - \sum_m \log\left(\frac{c_{m,n}}{p_{m,k}}\right)$
IS2	$\sum_m \frac{p_{m,k}}{h_{k,n}\,c_{m,n}} - \log\left(\frac{p_{m,k}}{h_{k,n}\,c_{m,n}}\right) - 1$	$\frac{1}{M}\sum_m \frac{p_{m,k}}{c_{m,n}}$	$M\log\left(\frac{1}{M}\sum_m \frac{p_{m,k}}{c_{m,n}}\right) - \sum_m \log\left(\frac{p_{m,k}}{c_{m,n}}\right)$
KL1	$\sum_m h_{k,n}\,c_{m,n}\log\left(\frac{h_{k,n}\,c_{m,n}}{p_{m,k}}\right) - h_{k,n}\,c_{m,n} + p_{m,k}$	$e^{-\sum_m c'_{m,n}\log\left(\frac{c_{m,n}}{p_{m,k}}\right)}$ with $c'_{m,n} = \frac{c_{m,n}}{\|\mathbf{c}_n\|_1}$	$1 - e^{-\sum_m c'_{m,n}\log\left(\frac{c'_{m,n}}{p_{m,k}}\right)}$ with $c'_{m,n} = \frac{c_{m,n}}{\|\mathbf{c}_n\|_1}$
KL2	$\sum_m p_{m,k}\log\left(\frac{p_{m,k}}{h_{k,n}\,c_{m,n}}\right) - p_{m,k} + h_{k,n}\,c_{m,n}$	$\frac{1}{\sum_m c_{m,n}}$	$\sum_m p_{m,k}\log\left(\frac{p_{m,k}}{c'_{m,n}}\right) - p_{m,k} + c'_{m,n}$ with $c'_{m,n} = \frac{c_{m,n}}{\|\mathbf{c}_n\|_1}$

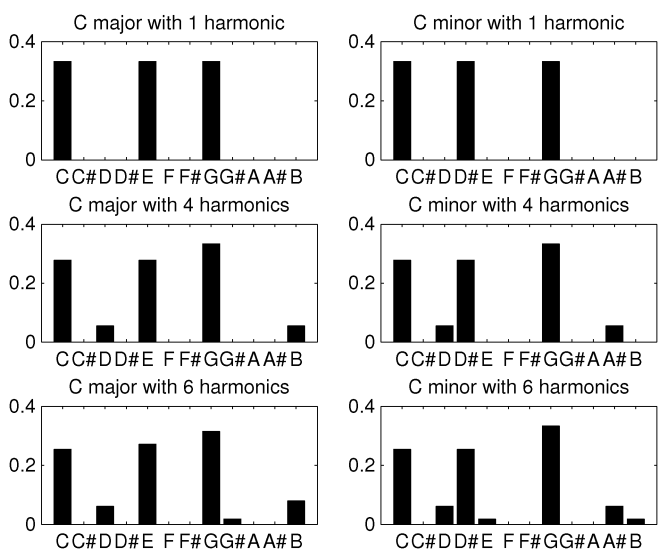

Fig. 1. Chord templates for C major/C minor with 1, 4, or 6 harmonics.

B. Chord Models

The chord templates are 12-dimensional vectors where each component represents the theoretical amplitude of each chroma in the chord. These chord templates can either be learned on audio data [6], [8], [9] or predetermined [1], [3], [5], [7], [10], [11]. However, Bello and Pickens [7] and Papadopoulos and Peeters [5] have shown that using fixed and musically inspired chord structures can give better results for the chord detection task. Besides, the use of fixed chord models allows to skip the time-consuming learning phase and the need of annotated training data.

In our system, three chord models are defined: examples for C major and C minor chords are displayed in Fig. 1.

The **first chord model** is a simple binary mask: an amplitude of 1 is given to the chromas defining the chord and an amplitude of 0 is given to the other chromas.[1] For example for a *C major* chord an amplitude of 1 is given to the chromas *C*, *E* and *G* while the other chromas have an amplitude of 0.

The **second chord model** is inspired from the work of Gomez [4] and Papadopoulos [5]. The information contained in a chromagram or any other spectral representation of a musical signal captures not only the intensity of every note but a blend of intensities for the harmonics of every note. It is therefore interesting and relevant to take into account the harmonics for each note of the played chord. An exponentially decreasing spectral profile is assumed for the amplitudes of the partials and an amplitude of s^{i-1} is added for the ith harmonic of every note in the chord. The parameter s is empirically set to 0.6. Our second chord model only takes into account the four first harmonics.

The **third chord model** is based on the same principle but takes into account the first six harmonics for the notes of the chord.

From these three chord models, we can build chord templates for all types of chords (major, minor, dominant seventh, diminished, augmented, etc.). By convention in our system, the chord templates are normalized so that the sum of the amplitudes is 1 but any other normalization could be employed.

C. Measures of Fit

1) Definitions: We consider for our recognition task several measures of fit, popular in the field of signal processing. Table I gives the expressions of these different measures, as well as the scale parameter analytically calculated from (2) and the final expression of the set of values $d_{k,n}$.

The well-known **Euclidean distance** (EUC) defined by

$$D_{EUC}(\mathbf{x}|\mathbf{y}) = \sqrt{\sum_m (x_m - y_m)^2} \tag{5}$$

[1]In practice, a small value is used instead of 0, to avoid numerical instabilities that may arise with some measures of fit, see Section III-C.

TABLE II
EXPRESSIONS OF THE MEASURES OF FIT ON TOY EXAMPLES ALONG WITH THEIR EQUIVALENT WHEN $\epsilon \to 0$

	EUC	IS1	IS2	KL1	KL2
Case 1	$1-\epsilon$ ~ 1	$\frac{1}{\epsilon}+\log(\epsilon)-1$ $\sim \frac{1}{\epsilon}$	$\epsilon-\log(\epsilon)-1$ $\sim -\log\epsilon$	$\epsilon-\log(\epsilon)-1$ $\sim -\log\epsilon$	$\epsilon\log(\epsilon)-\epsilon+1$ ~ 1
Case 2	$1-\epsilon$ ~ 1	$\epsilon-\log(\epsilon)-1$ $\sim -\log\epsilon$	$\frac{1}{\epsilon}+\log(\epsilon)-1$ $\sim \frac{1}{\epsilon}$	$\epsilon\log(\epsilon)-\epsilon+1$ ~ 1	$\epsilon-\log(\epsilon)-1$ $\sim -\log\epsilon$

has already been used by Fujishima [1] for the chord recognition task.

The **Itakura–Saito divergence** [12] defined by

$$D_{IS}(\mathbf{x}|\mathbf{y}) = \sum_m \frac{x_m}{y_m} - \log\left(\frac{x_m}{y_m}\right) - 1 \tag{6}$$

was presented as a measure of the goodness of fit between two spectra and became popular in the speech community during the 1970s. This is not a distance, since it is in particular not symmetrical.[2] It can therefore be calculated in two ways: $D(h_{k,n}\mathbf{c}_n|\mathbf{p}_k)$ will define *IS1*, while $D(\mathbf{p}_k|h_{k,n}\mathbf{c}_n)$ will define *IS2*.

The **Kullback–Leibler divergence** [13] measures the dissimilarity between two probability distributions. It has been widely used in particular in information theory and has given rise to many variants. In the present paper we use the generalized Kullback–Leibler divergence defined by

$$D_{KL}(\mathbf{x}|\mathbf{y}) = \sum_m x_m \log\left(\frac{x_m}{y_m}\right) - x_m + y_m. \tag{7}$$

Just like Itakura–Saito divergence [12], the generalized Kullback–Leibler divergence is not symmetrical, so that we can introduce two measures of fit: $D(h_{k,n}\mathbf{c}_n|\mathbf{p}_k)$ *(KL1)* and $D(\mathbf{p}_k|h_{k,n}\mathbf{c}_n)$ *(KL2)*.

While the Euclidean distance had already been used for the chord recognition task, the use of Itakura–Saito and Kullback–Leibler divergences is innovative. The non-symmetry of these divergences allows to define two variants (*IS1* and *IS2* and *KL1* and *KL2*). We shall now investigate the properties of these two variants and interpret them in our chord recognition context.

Considering the variations of the functions of two variables $D_{IS}(x|y)$ and $D_{KL}(x|y)$, we notice that the terms $D_{IS}(x|y)$ and $D_{KL}(x|y)$ take high values when x is large and y is close to 0. The *IS1* and *KL1* measures of fit being just sums of 12 of these terms, we can deduce that a high value of *IS1* or *KL1* would be obtained if, for at least one of the chromas, the first term $h_{k,n}c_{m,n}$ is larger that the $p_{m,k}$ term. That is to say if the chroma does not belong to the chord template but is present in the chromagram frame. This means that the *IS1* and *KL1* measures of fit reject in priority chords whose null chromas are nevertheless present in the chroma vector.

On the contrary, the terms $D_{IS}(y|x)$ and $D_{KL}(y|x)$ take high values when x is close to 0 and y is large. Therefore, a high value of *IS2* or *KL2* is obtained when, for at least one of the chromas, $h_{k,n}c_{m,n}$ is lower that $p_{m,k}$. That is to say if the chroma is present in the chord template but not in the chromagram frame. This means that the *IS2* and *KL2* measures of fit reject in priority chords whose notes are not all present in the chroma vector.

2) Toy Examples: Let us check these assumptions on a very simple toy example. Let us suppose that we want to find a C major chord in a chromagram frame $\mathbf{x}$. The chord template can be written $\mathbf{y} = [1, \epsilon, \epsilon, \epsilon, 1, \epsilon, \epsilon, 1, \epsilon, \epsilon, \epsilon, \epsilon]$ with ϵ being a very small value used to avoid numerical instabilities.

- Case 1 (extra note): The chromagram frame is a C major chord, with an extra D

$$\mathbf{x} = [1, \epsilon, 1, \epsilon, 1, \epsilon, \epsilon, 1, \epsilon, \epsilon, \epsilon, \epsilon].$$

- Case 2 (missing note): The chromagram frame is a C5 chord (only C and G)

$$\mathbf{x} = [1, \epsilon, \epsilon, \epsilon, \epsilon, \epsilon, \epsilon, 1, \epsilon, \epsilon, \epsilon, \epsilon].$$

Table II shows the expressions of the measures of fit calculated for each of these toy examples along with their equivalent when $\epsilon \to 0$. We observe that in Case 1, for a very small value of ϵ, the *IS1* measure of fit tends to be very high, *IS2* and *KL1* are finite,[3] and *KL2* is close to 1. This indicates that *IS1* strongly reacts to the presence of parasite notes in the chroma vector, while it does not make a big difference for *KL2*. On the contrary, in Case 2, the *IS2* measure of fit is really sensitive to the fact that all the notes within the chord template can be found in the chroma vector, while *KL1* is not too affected.

D. Filtering Methods

So far, our chord detection is performed frame-by-frame without taking into account the results on adjacent frames. In practice, it is rather unlikely for a chord to last only one frame. Furthermore, the information contained in the adjacent frames can help decision [14]: it is one of the main advantages of the methods using HMM, where the introduction of transition probabilities naturally leads to a smoothing effect. Nevertheless, HMM-based methods inherently assume an exponentially temporal distribution, which does not suit well the rhythmic structure of pop songs [15]. We therefore propose, as a third block for our method, to use an *ad hoc* filtering process which implicitly informs the system of the expected chord duration. The post-processing filtering is applied upstream to the calculated measures. Note that the use of this *ad hoc* filtering process is innovative, since it had been previously applied to chromagrams [1], [7], [16] or detected chord sequences [7], but never to the recognition criterion itself.

We introduce new criteria $\tilde{d}_{k,n}$ based on L successive values centered on frame n (L is then odd). These $\tilde{d}_{k,n}$ are calculated

[2]Symmetrized versions of Itakura–Saito and Kullback–Leibler were first considered but since they prevented any analytical calculation of $h_{k,n}$, we preferred to avoid the numerical optimization that would become necessary and possibly lengthy.

[3]In practice we use $\epsilon = 10^{-16}$.

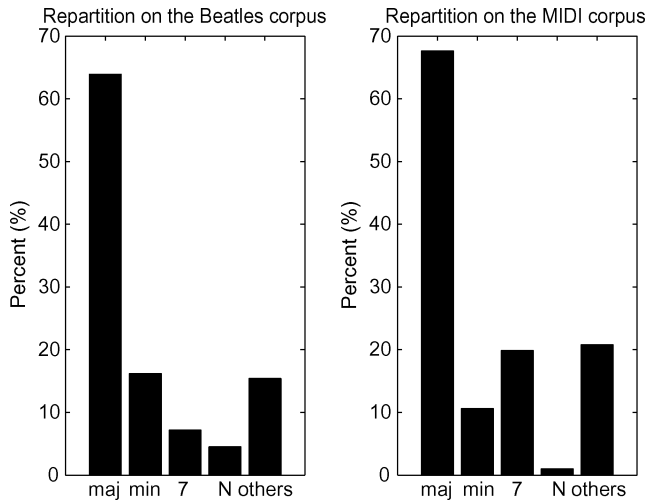

Fig. 2. Statistics on the Beatles and the MIDI corpus: distribution of the chord types as percentage of the total duration.

from the $d_{k,n}$ previously calculated on the L adjacent frames, as shown below. In our system two types of filtering are tested.

The **low pass filtering** defined by

$$\tilde{d}_{k,n} = \frac{1}{L} \sum_{n'=n-\frac{L-1}{2}}^{n+\frac{L-1}{2}} d_{k,n'} \tag{8}$$

tends to smooth the output chord sequence and to reflect the long-term trend in the chord change.

The **median filtering** defined by

$$\tilde{d}_{k,n} = \mathrm{med}\{d_{k,n'}\}_{n-\frac{L-1}{2} \le n' \le n+\frac{L-1}{2}} \tag{9}$$

has been widely used in image processing and is particularly efficient to correct random errors. Furthermore, this filtering has the property of respecting transitions.

In every case, the detected chord $\hat{k}_n$ on frame n is the one that minimizes the set of values $\{\tilde{d}_{k,n}\}_k$

$$\hat{k}_n = \arg\min_k \tilde{d}_{k,n}. \tag{10}$$

IV. Evaluation and Corpus

A. Beatles Corpus

Our first evaluation database is made of the 13 Beatles albums (180 songs, PCM 44 100 Hz, 16 bits, mono). This database is in particular the one used in MIREX 08 for the Audio Chord Detection task.[4] The evaluation is realized thanks to the chord annotations of the 13 Beatles albums kindly provided by Harte and Sandler [17]. In these annotation files, 17 types of chords are present (maj, dim, aug, maj7, 7, dim7, hdim7, maj6, 9, maj9, sus4, sus2, min, min7, minmaj7, min6, min9) and one "no chord" label (N) corresponding to silences or untuned material. The alignment between annotations and wave files are done with the algorithm provided by Christopher Harte.

Fig. 2 represents the distribution of the durations of the different chord types on the Beatles corpus. The most common chord types in the corpus are major, minor, dominant seventh, "no chord" states, minor seventh and ninth. Any other chord type represents less than 1% of the total duration.

[4]http://www.music-ir.org/mirex/wiki/2008:Audio_Chord_Detection

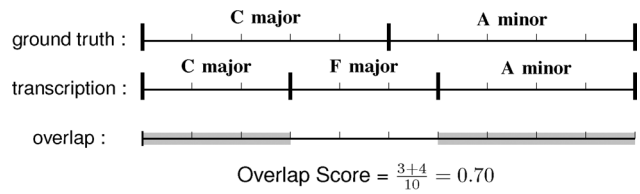

Fig. 3. Example of calculation of an overlap score.

B. QUAERO Corpus

The second corpus was provided to us within the QUAERO project.[5] It consists of 20 real audio songs annotated by IRCAM (PCM 22050 Hz, 16 bits, mono) from various artists (Pink Floyd, Queen, Buenavista Social Club, Dusty Springfield, Aerosmith, Shack, UB40, Fall Out Boy, Nelly Furtado, Justin Timberlake, Mariah Carey, Abba, Cher, Phil Collins, Santa Esmeralda, Sweet, FR David, and Enya) and various genres (pop, rock, electro, salsa, disco, etc.). The corpus only contains major (88%), minor (10.7%) and "no chord" (1.3%) labels.

C. MIDI Corpus

Our third evaluation database is composed of 12 songs from various artists in different genres (blues, country, pop, and rock). The audio files (PCM 44 100 Hz, 16 bits, mono) are synthesized from MIDI files[6] using the free software Timidity ++.[7] Timidity ++ is a software synthesizer which can generate realistic audio data from MIDI files using a sample-based synthesis method. We have manually annotated the songs: five types of chords are present (maj, min, 7, sus2, sus4) as well as the "no chord" label (N). The distribution of the durations of the different chord types on the MIDI corpus is displayed in Fig. 2.

D. Evaluation Method

The evaluation method used in this paper corresponds to the one used in MIREX 08 for the Audio Chord Detection task.

This evaluation protocol only takes into account major and minor chord types. The 17 types of chords present in the annotation files are therefore first mapped into major and minor types following these rules:

- major: maj, dim, aug, maj7, 7, dim7, hdim7, maj6, 9, maj9, sus4, sus2
- minor: min, min7, minmaj7, min6, min9

For the systems detecting more chord types (dominant seventh, diminished, etc.), once the chords have been detected with their appropriate models, they are then mapped to the major and minor following the same rules than for the annotation files.

An *Overlap Score (OS)* is calculated for each song as the ratio between the lengths of the correctly analyzed chords and the total length of the song. We define for the Beatles corpus an *Average Overlap Score (AOS)* which is obtained by averaging the Overlap Scores of all the 180 songs of the corpus. An example of calculation of an Overlap Score is presented in Fig. 3.

E. Input Features

Based on preliminary experiments we chose among three types of chromagram [7], [16], [18], the one proposed by Bello

[5]QUAERO project: http://www.quaero.org.

[6]The MIDI files were obtained on http://www.mididb.com.

[7]The software is freely downloadable on http://timidity.sourceforge.net.

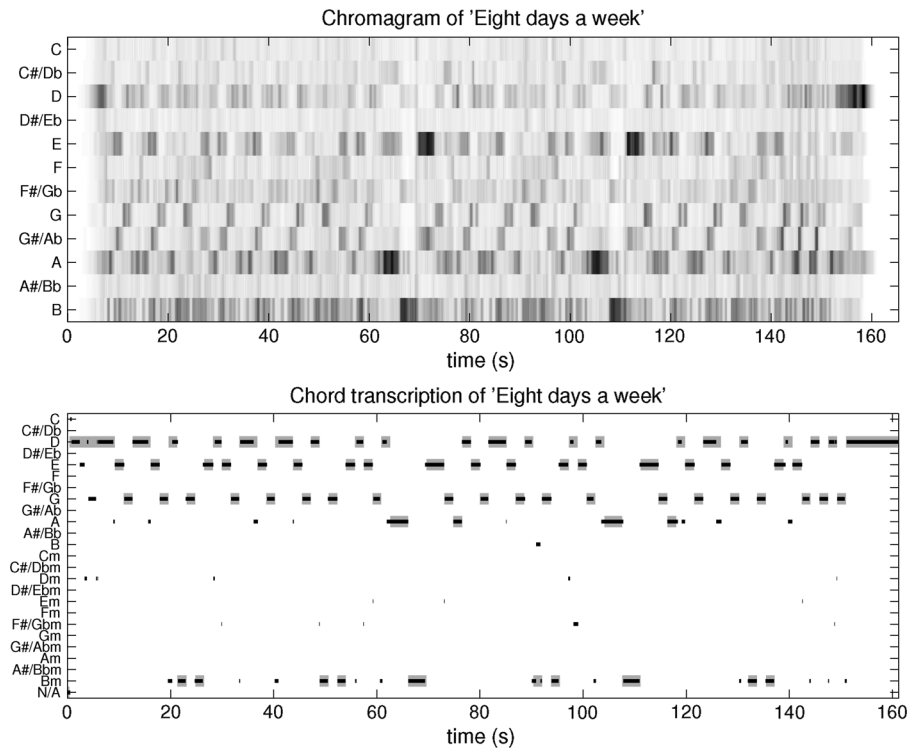

Fig. 4. Chromagram and chord transcription for the song *Eight days a week* by The Beatles. At the bottom the estimated chord labels are in black while the ground-truth chord annotation is in gray.

TABLE III
AVERAGE OVERLAP SCORES ON THE 13 BEATLES ALBUMS

	no filtering			low-pass filtering			median filtering		
	1 harm.	4 harm.	6 harm.	1 harm.	4 harm.	6 harm.	1 harm.	4 harm.	6 harm.
EUC	0.665	0.636	0.588	0.710	0.684	0.646	0.705	0.679	0.636
IS1	0.665	0.441	0.399	0.706	0.460	0.415	0.706	0.465	0.422
IS2	0.657	0.667	0.170	0.704	0.713	0.178	0.703	0.714	0.178
KL1	0.665	0.487	0.140	0.700	0.532	0.151	0.692	0.498	0.143
KL2	0.667	0.672	0.612	0.709	0.712	0.648	0.714	**0.718**	0.656

and Pickens [7], which appeared to give the best results for our chord transcription task. The Constant-Q Transform [2] allowing a frequency analysis on bins centered on logarithmically spaced frequencies is used. The center frequency f_k of the kth bin is indeed defined as

$$f_k = 2^{\frac{k}{b}} f_{min} \tag{11}$$

where b represents the number of bins per octave and f_{min} the frequency where the analysis starts.

The signal is first downsampled to 5512.5 Hz and the CQ-Transform is calculated with $b = 36$ (3 bins per semi-tone), between frequencies 73.42 Hz (D2) and 587.36 Hz (D5). These parameters lead to a window length of 4096 samples and the hop size is set to 512 samples.

Thanks to the 36 bins per octave resolution, a tuning algorithm [3] can be used. After a pick detection in the chromagram, a correction factor is calculated so as to take into account the detuning. A median filtering is finally applied in order to eliminate too sharp transitions (eight frames).

Some details about the calculation of the chromagram can be found in [7]. We used the code kindly provided by the authors. The silence ("no chord") detection is done by an empirically set threshold on the energy of the chroma vectors.

An example of chromagram and chord transcription is displayed on Fig. 4.

V. RESULTS ON THE AUDIO CORPUS

The previously described five measures of fit (*EUC*, *IS1*, *IS2*, *KL1*, and *KL2*), three chord models (1, 4, or 6 harmonics) and two filtering methods (low-pass and median) with neighborhood sizes from $L = 1$ to $L = 25$ are tested. These 375 parameter sets can be seen as so many chord recognition systems. We now investigate the systems giving the best results on the Beatles corpus.

A. Results With Major/Minor Chord Types

Average Overlap Scores on the 13 Beatles albums are presented in Table III with the major/minor templates. For sake of conciseness, we only displayed the results for the optimal choice

of L. The best average result is obtained with the *KL2*, the four harmonics chord model and the median filtering with $L = 15$ giving a recognition rate of 71.8%.

Interestingly, we notice that for the *EUC*, *IS1*, and *KL1* measures of fit, the results worsen when we increase the number of harmonics. We propose here two explanations for these results. In the particular cases of *IS1* and *KL1*, this can be explained by the fact that they both contain a logarithm component which is sensitive to the zeros within chord templates. We have seen in Section III-C that these measures of fit categorize chords by comparing every null chroma within the chord template to its value in the chroma vector. Since chord models with high number of harmonics contain less null chromas (see Fig. 1), the discrimination between chords is harder, which results in worse scores. A more general explanation for this phenomenon can be found by relating back to the notion of chord template itself. As such, a chromagram frame is very hard to characterize: it is supposed to only contain the notes played by the instruments, but in reality it also captures noise or drums. Furthermore, it also depends on instrument timbres and on the relative amplitudes of the played notes. The question is: what kind of templates should we use in order to only capture useful information from these chroma vectors? The exponential model introduced in harmonic-dependent templates is supposed to better suit the reality of music, but it also degrades the chord templates, by making less clear what they are supposed to capture. By introducing notes which are not explicitly present in the chord, the templates may detect notes which are actually due to noise, drums, or even melody. Indeed, our results show that the only cases where the harmonic chord templates perform well are the *IS2* and *KL2* with four harmonics and still the differences between these scores and those obtained with only one harmonic are very small.

A pathological situation appears when using the Itakura–Saito divergences *IS1* and *IS2* with the six harmonics chord model. Indeed, we observe that the use of *IS2* with the six harmonics chord model leads to a systematic detection of minor chords, while the *IS1* measure with six harmonics chord model only detects major chords. In the case of the *IS1* the loss in scores is less noticeable, because of the high number of major chords in the Beatles corpus. We believe that the explanation of this phenomena lies in the structure of the 6 harmonics chord model. Indeed, the six harmonics chord model gives a different number of null components for the major and minor chords: we can see in Fig. 1 that the major chord model has six null components while the minor chord has five null components. The recognition criterion associated to the *IS2* has the property that given a chroma vector, the more zeros in the chord template $\mathbf{p}_k$, the larger the value of the criterion. This measure of fit will therefore always give larger values for the chord models having more null components, that is to say the major chords, which leads to a systematic detection of only minor chords. The same phenomenon can be observed for the *IS1* measure of fit, this time with a systematic detection of major chords.

Both low-pass filtering and median filtering give good results: the low-pass filtering tends to smooth the chord sequence while the median filtering reduces the random errors. In most cases the optimal value of L lies between 13 and 19 which corresponds, with our window parameters, to a length of approximately 2 seconds. Nevertheless, while post-processing methods inform our systems about the expected chord length, we still notice that our transcriptions are sometimes fragmented (see Fig. 4). While these fragmented chords, thanks to their short duration, do not penalize much the recognition scores, they degrade the transcription by making it less clear and readable.

Some songs give disappointing results (<0.100) with all parameter sets: it is often due either to a strong detuning which is too large to be corrected by the tuning algorithm present in the chromagram computation (e.g., *Wild Honey Pie, Lovely Rita*), or to untuned material such as spoken voice, non-harmonic instruments or experimental noises (applause, screams, car noise, etc.) (e.g., *Revolution 9*).

B. Results With Other Chord Types

The simplicity of our method allows to easily introduce chord templates for chord types other than major and minor: we study here the influence of the chord types considered over the performances of our system.

The choice of the introduced chord types is guided by the statistics on the corpus previously presented. We introduce in priority the most present chords of the corpus: dominant seventh (7), minor seventh *(min7)* and ninth (9). The best results are obtained by detecting major, minor and dominant seventh chords, with the KL2, the one harmonic chord model and the median filtering with $L = 17$ giving a recognition rate of 72.4%. The introduction of dominant seventh chords, which are very present in the Beatles corpus, clearly enhances the results. Yet, these results should be tempered: indeed, when our Maj-Min-7 method detects a chord as dominant seventh, it is right in only 9.2% of the cases. Most of the time (53.8%) the ground-truth chord is in reality the associated major chord. The dominant seventh template therefore helps the detection of major chords. It means that often, when our Maj-Min-7 gives better results that our Maj-Min method, it is due to the detection of major chords which would not have been detected with the Maj-Min method.

The introduction of more chord types which are less present (minor seventh, ninth) degrades the results (70.6% for Maj-Min-7-Min7 and 70.6% for Maj-Min-7-Min7-9). Indeed, the introduction of a model for a new chord type gives a better detection for chords of this type but also leads to new errors such as false detections. Therefore, only frequent chord types should be introduced, ensuring that the enhancement caused by the better recognition of these chord types is larger than the degradation of the results caused by the false detections.

C. Comparison With the State-of-the-Art

Our method is now compared to the following methods that entered MIREX 08.

Bello & Pickens (BP) [7] use 24-states HMM with musically inspired initializations, Gaussian observation probability distributions and EM-training for the initial state distribution and the state transition matrix.

Ryynänen & Klapuri (RK) [8] use 24-states HMM with observation probability distributions computed by comparing low and high-register profiles with some trained chord profiles.

TABLE IV
COMPARISON WITH THE STATE-OF-THE-ART

	Beatles corpus		Quaero corpus	
	AOS	Time	AOS	Time
Our method (Maj-Min)	0.718	790s	0.706	95s
Our method (Maj-Min-7)	**0.724**	796s	0.682	97s
Bello & Pickens (BP)	0.707	1619s	0.699	261s
Ryynänen & Klapuri (RK)	0.705	2241s	**0.730**	350s
Khadkevich & Omologo (KO)	0.663	1668s	0.503	255s
Pauwels, Varewyck & Martens (PVM)	0.647	12402s	0.664	2684s

EM-training is used for the initial state distribution and the state transition matrix.

Khadkevich & Omologo (KO) [19] use 24 HMMs: one for every chord. The observation probability distributions are Gaussian mixtures and all the parameters are trained through EM.

Pauwels, Verewyck, & Martens (PVM) [20] use a probabilistic framework derived from Lerdahl's tonal distance metric for the joint tasks of chords and key recognition.

These methods have been tested with their original implementations and evaluated with the same protocol (AOS). We tested the methods on the Beatles and Quaero corpus. Results of this comparison with the state-of-the-art are presented in Table IV.

First of all, it is noticeable that all the methods give rather close results on the Beatles corpus: there is only a 8% difference between the methods giving the best and worse results. This is likely to be partially due to the fact that this database is the largest annotated database available and is commonly used by all researchers working on chord recognition, either to tune some parameters, train their methods or simply to test if their method works. In particular, the RK and KO methods are both pre-trained on the Beatles corpus. We can observe that our two methods give the best AOS on this corpus. Yet, since all the scores are close, we propose to perform a Friedman and a Tukey–Krammer test (see [21], [22] for details), in order to figure out whether there are significant differences between the tested chord recognition methods. Results are presented on Fig. 5: it appears that our Maj-Min method is significantly better from two other tested methods (KO and PVM), while our Maj-Min-7 method is significantly better than three methods (RK, KO, and PVM).

Interestingly, results on the Quaero corpus are more contrasted: in particular KO gives lower scores while RK obtain here the best results. This result is actually surprising, since both these methods use models which are trained on Beatles data and yet they respond differently to the new corpus ($+0.025$ for RK and -0.160 for KO). It is interesting to see that our methods, while not giving the best scores anymore, still performs well on this corpus: our Maj-Min method indeed gives the second best result on this corpus. The larger gap for Maj-Min-7 can be explained by the fact that the introduction of dominant seventh chords tend to overestimate the number of major chords (see Section V-A) and that the Quaero corpus contain less major chord that the Beatles corpus (see Section IV-B).

Concerning the choice of parameters, experimental results show that for the Maj-Min method, the AOS obtained with the optimal parameters is 0.709 (against 0.706 with the default

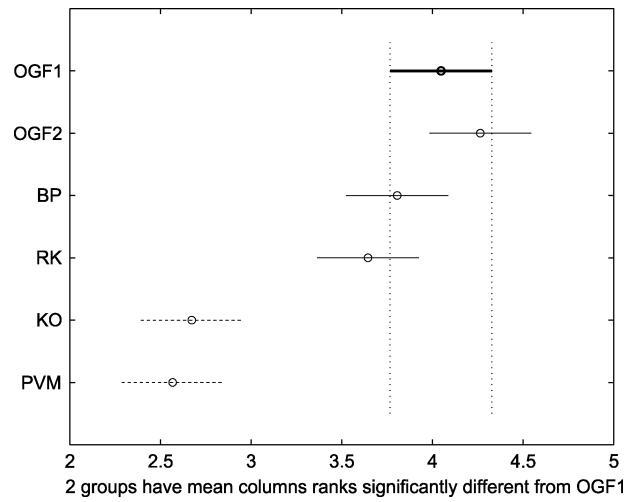

Fig. 5. Tukey–Kramer's test performed on overlap scores calculated on the Beatles corpus. On this figure, the x-axis shows the average rank of each chord recognition method along with its confidence interval. Ranks are presented in ascending order and two mean ranks are significantly different if their confidence intervals are disjoint.

Maj-Min parameters) and for the Maj-Min-7 method, the optimal score is 0.695 (while it is 0.682 with the default parameters). These good performances show that our parameters choice, while undeniably being optimal for the Beatles corpus, also fits well other genres or styles of music.

Our methods are also characterized by a very low computational time. They are indeed twice as fast as the best state-of-the-art method (Bello and Pickens).

Besides this evaluation on these two corpus, our methods have also taken part in the MIREX 2009 evaluation on the Audio Chord Detection task for the pre-trained systems.[8] The evaluation corpus was not only composed by the Beatles songs but also 36 songs from Queen and Zweieck. While once again the scores are very close, our Maj-Min-7 and Maj-Min methods gave respectively the second and fourth best Average Overlap Scores for the major-minor chord recognition task and reached the first and second places for the root detection task. The trained systems gave better scores that pre-trained systems but also our Maj-Min-7 method gives the same score for the root detection than the best trained system [23] (using SVM classifiers): this shows that it is really hard to draw conclusions on the influence of training.

D. Analysis of the Errors

In most chord transcription systems, the errors are often caused by the harmonic proximity or the structural similarity (common notes) between the real chord and the wrongly detected chord.

Harmonic Proximity: Errors can be caused by the harmonic proximity between the original and the detected chord, that is to say chords which have a particular relationship involving harmony, key, etc. Fig. 6 pictures the doubly nested circle of fifths which represents the major chords (capital letters), the minor chords (lower-case letters) and their harmonic relationships. The distance linking two chords on this doubly nested circle of fifths is an indication of their harmonic proximity.

[8]http://www.music-ir.org/mirex/wiki/2009:Audio_Chord_Detection

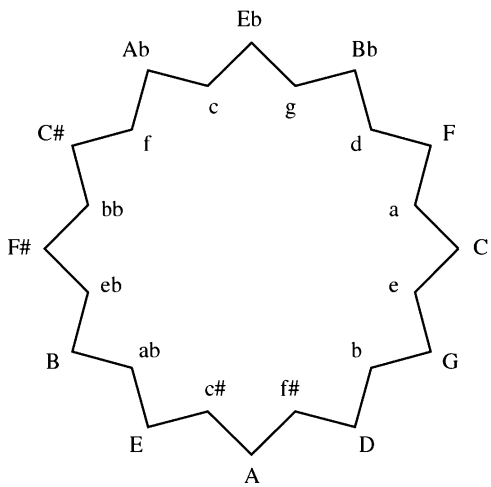

Fig. 6. Doubly nested circle of fifths [7].

TABLE V
PARTICULAR RELATIONSHIPS BETWEEN CHORDS AND POTENTIAL SOURCES OF ERRORS: EXAMPLES FOR C MAJOR AND C MINOR CHORDS

Reference chord	**C**	**Cm**
parallel	Cm	C
relative (submediant)	Am	A♭
mediant	Em	E♭
subdominant	F	Fm
dominant	G	Gm

Given a major or minor chord, the four closest chords on this circle are the relative (submediant), mediant, subdominant, and dominant.

Structural Similarity: Two chords are also likely to be mistaken one for another when they *look alike*, that is to say, when they share notes (especially in template-based systems). Given a major or minor chord, there are three chords which have two notes in common with this chord: the parallel minor/major, the relative minor/major (or submediant) and the mediant chord. Note that these two last chords are also harmonically close to the original chord. These types of errors are very likely to occur in template-based methods, which does not extract harmonic structure information from the music piece.

We have therefore brought out five potential sources of errors among the 23 possible ones (i.e., the 23 other wrong candidates for one reference chord). Some of these errors seem specific to the template-based systems, while the others seem to apply to every chord recognition system. Examples of these potential sources of errors for C major and C minor chords are displayed in Table V.

Fig. 7 displays the distribution of these error types as a percentage of the total number of errors for every evaluated method. Errors due to the bad detection of the "no chord" states are represented with the "no chord" label.

The main sources of errors correspond to the situations previously described and to the errors caused by silences ("no chord"). Actually, in most methods, the five types of errors previously considered (over the 23 possible ones) represent more than half of the errors.

As expected, our methods have the largest parallel errors percentage (with the exception of the RK method), which is probably due to the fact that we work with chord templates and therefore do not detect any harmonic features such as key, harmony, chord vocabulary, etc. Furthermore, for our methods (and the RK method), the percentages of errors due to structural similarity and harmonic proximity are the same, while for all other tested methods, the proportion of harmonic proximity errors is larger. This is actually very surprising that the method proposed by Ryynänen and Klapuri has a error distribution very close to our Maj-Min method, while being based on training.

Among interesting results, one can notice that the introduction of the dominant seventh chords clearly reduces the proportion of the errors due to relative (submediant) and mediant (-11%).

Finally, Pauwels, Varewyck, and Martens' system is clearly mostly penalized by the wrong detection of the "no chord" states, when Khadkevich and Omologo's method produces a uniformly distributed range of errors.

VI. RESULTS ON THE MIDI CORPUS

We now use the two sets of parameters described in the previous section for the Maj-Min (*KL2, 4 harmonics, median filtering with* $L = 15$) and the Maj-Min-7 (*KL2, 1 harmonic, median filtering with* $L = 17$) chord detection systems on the MIDI corpus.

A. Influence of the Music Genre

Table VI shows the Overlap Scores for the 12 songs of the MIDI corpus for the Maj-Min and the Maj-Min-7 chord recognition methods. Besides the results obtained with the default parameters, we also displayed the results with the optimal parameters in order to evaluate the fitness of our default parameters.

The first thing we can observe is that the scores obtained with the default parameters are rather close to the best ones. This shows that the parameters we deduced from the Beatles corpus can be used in a more general context.

We can also see that the scores are all creditable. This can surely be explained by the fact that we work here with resynthesized wave files and not real audio. These audio files are indeed generated with instrument patterns which contain less noise and untuned material than real instrument recordings.

Genre does not seem to have an influence on the scores. Nevertheless, the scores obtained on country songs are particularly large, but it is probably due to the very simple chord structures of these songs (mainly alternation of three chords).

B. Influence of the Percussive Noise

Our method strongly relies on the chromagram, that is to say a harmonic representation of the music. It can therefore be thought that inharmonic components of the music, for example drums, tend to add noise to the chromagram, which can lead to errors in the chord detection.

Working with audio data computed from MIDI files gives us the chance to synthesize them without the percussive parts. Indeed, the software Timidity ++ allows to mute one channel (instrument) for the wave-synthesis of the MIDI file.

The same simulations have been performed with these drum-free audio files. The removal of the percussions does not improve significantly the Overlap Scores. Indeed, the average

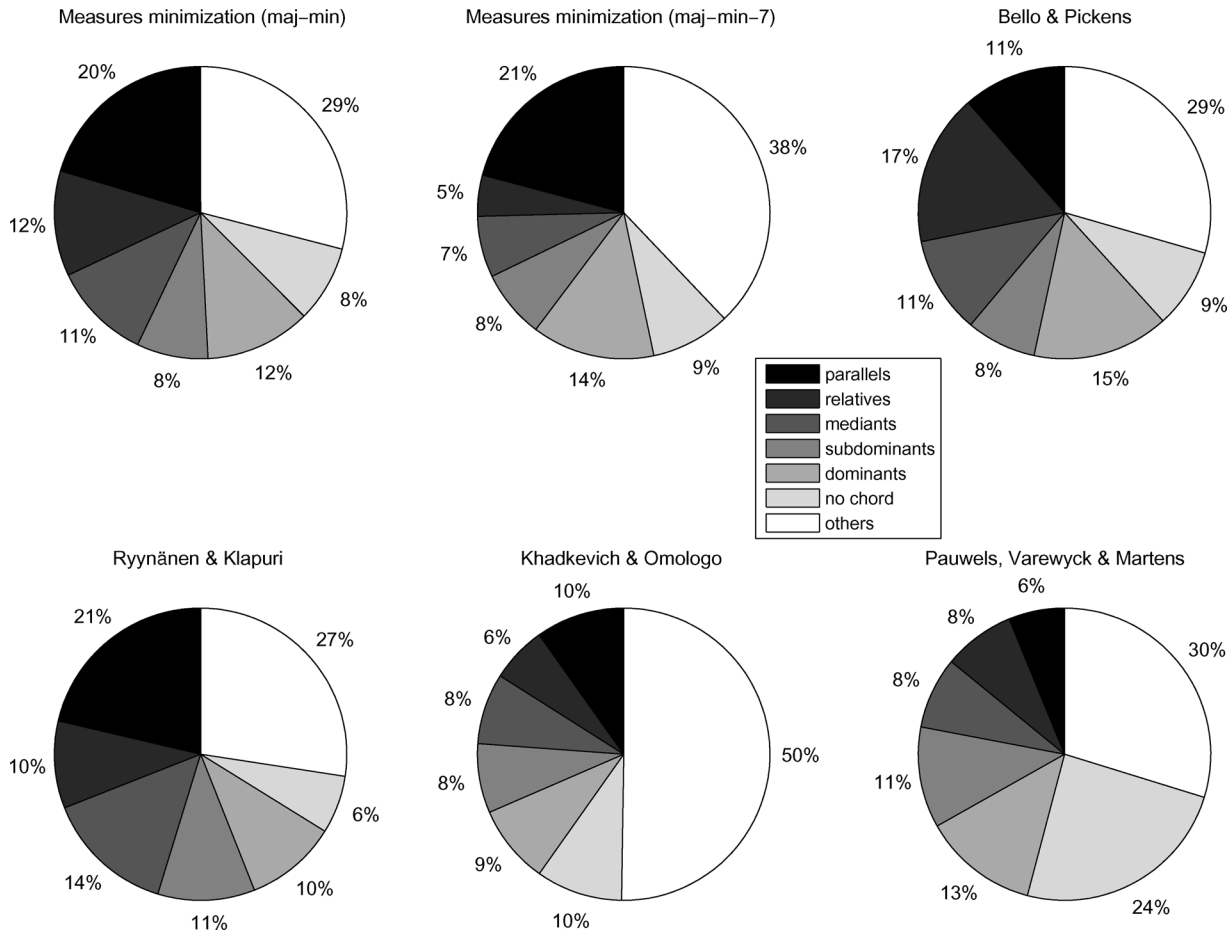

Fig. 7. Distribution of the errors as a percentage of the total number of errors.

TABLE VI
OVERLAP SCORE FOR THE 12 SONGS OF THE MIDI CORPUS

		Maj-Min		Maj-Min-7	
	Song title	Default	Optimal	Default	Optimal
Country	Ring of fire *(Johnny Cash)*	0.844	0.918	0.848	0.924
	Tennessee waltz *(Roy Acuff)*	0.941	0.955	0.949	0.955
	Stand by your man *(Tammy Wynette)*	0.895	0.909	0.902	0.911
Pop	Dancing queen *(ABBA)*	0.786	0.804	0.728	0.782
	I drove all night *(Cyndi Lauper)*	0.870	0.891	0.856	0.889
	Born to make you happy *(Britney Spears)*	0.867	0.892	0.861	0.892
Blues	Blues stay away from me *(The Delmore Brothers)*	0.630	0.791	0.854	0.912
	Boom, boom, boom *(John Lee Hooker)*	0.839	0.903	0.876	0.913
	Keep it to yourself *(Sonny Boy Williamson)*	0.771	0.909	0.907	0.928
Rock	Twist and shout *(The Beatles)*	0.827	0.892	0.850	0.901
	Let it be *(The Beatles)*	0.835	0.876	0.876	0.880
	Help ! *(The Beatles)*	0.918	0.920	0.899	0.918

score improvement is only 0.8% as well with the Maj-Min system than with the Maj-Min-7. We believe that the noise contained in the chromagram, which lead to errors, is not only due to drums but also, for example, to the melody itself, since it does not only play notes contained in the chord pattern.

C. Beat Synchronous Chord Detection

The filtering process we have been using so far has a fixed length predetermined by the system parameters. It seems interesting to introduce beat information either in the chromagram computation or in the recognition criteria. For our tests we used the beat-detection algorithm provided by Davies and Plumbley [24].

The first way to take into account the beat information is to compute a beat-synchronous chromagram, that is to say averaging the chromagram over the number of frames representing a beat time. This process has already been used by Bello and Pickens [7]. Yet this does not improve the results: comparing

the best results obtained with the usual chromagram and those obtained with the beat-synchronous one, it appears that the average degradation is −6% for the Maj-Min and −7% for the Maj-Min-7 system.

The second way to integrate this information is to filter the recognition criteria (either with the low-pass or the median filtering method) with a neighborhood size equal to the beat time. Even if the degradation is lower than with the beat-synchronous chromagram, the results are also penalized: the average degradation is −2% for the Maj-Min and the −4% for the Maj-Min-7 system.

We believe that these disappointing results are probably due to the fact that the beat detection does not take into account the distinction between on-beats and off-beats. Indeed, the chord change tend to occur mainly on the on-beats and not on every beat. Averaging either the chromagram or the recognition criteria on every beat does not really capture the rhythmic information.

VII. Conclusion

In this paper, we have presented a fast and efficient chord recognition method. The main innovative idea is the joint use of popular measures which had never been considered for this task and filtering methods taking advantage of time persistence. The decoupling of various stages of the chord template matching process enables to achieve high effectiveness in less time. Our system also offers a novel perspective about chord detection, which distinguishes from the predominant HMM-based approaches.

Since our method is only based on the chromagram no information about style, rhythm, or instruments is needed so that our recognition system would work with any type of music. Furthermore we do not require any training on any database, which enables the computation time to be kept really low.

Acknowledgment

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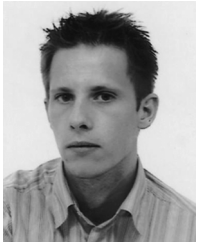

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Dr. Grenier has been co-chairman of the "Tenth International Workshop on Acoustic Echo and Noise Control" (IWAENC 2006). He has been technical co-chair of the "2010 IEEE International Workshop on Multimedia Signal Processing" (MMSP 2010).

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