Musical Genre Classification

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G. Tzanetakis and P. Cook, "Musical genre classification of audio signals," IEEE Trans. on Speech and Audio Processing, vol. 10, no. 5, 2002, pp. 293-302.

Introduction

- The members of a particular genre share certain characteristics
- Automatic musical genre classification
  - Music information retrieval
  - Developing and evaluating features that can be used in similarity retrieval, classification, segmentation, and audio thumbnailing

Related Work

- Audio classification has a long history originating from speech recognition
  - Classify audio signals into music, speech, and environmental sounds
  - Classify musical instrument sounds and sound effects
- The features they used are not adequate for automatic musical genre classification

Feature Extraction

- Timbral Texture Features
  - spectral centroid, spectral rolloff, spectral flux, zero-crossing rate, MFCC, energy
- Rhythmic Content Features
- Pitch Content Features

Spectral Centroid

- The center of gravity of the magnitude spectrum of short-time Fourier transform (STFT)

$$C_t = \frac{\sum_{n=1}^{N} M_t[n] * n}{\sum_{n=1}^{N} M_t[n]}$$

$M_t[n]$ is the magnitude of the Fourier transform at frame t and frequency bin n

- A measure of spectral shape and higher centroid values correspond to “brighter” textures with high frequencies

Spectral Rolloff

- The frequency R_t such that

$$\sum_{n=1}^{R_t} M_t[n] = 0.85 * \sum_{n=1}^{N} M_t[n]$$

- A measure of the "skewness" of the spectral shape
- It is used to distinguish voiced from unvoiced speech and music. (unvoiced speech has a high proportion of energy contained in the high-freq. range of the spectrum)

Spectral Flux

- Squared difference between the normalized magnitudes of successive spectral distributions

$$F_t = \sum_{n=1}^{N} (N_t[n] - N_{t-1}[n])^2$$

$N_t[n]$ and $N_{t-1}[n]$ are the normalized magnitude of the Fourier transform at frames t and $t-1$

- A measure of the amount of local spectral change

Zero-Crossing Rate

- A measure of the noisiness of the signal

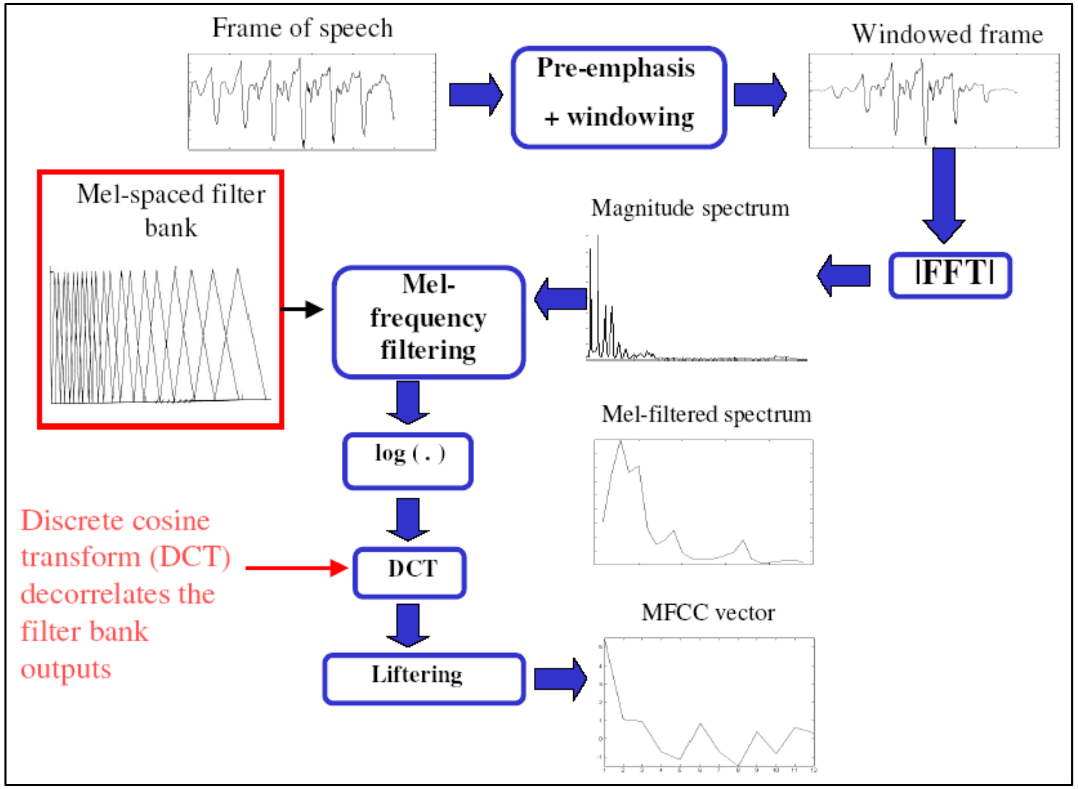
$$Z_t = \frac{1}{2} \sum_{n=1}^{N} \left| sign(x[n]) - sign(x[n-1]) \right|$$

sign function is 1 for positive arguments and 0 for negative arguments
x[n] is the time domain signal for frame *t*

- Unvoiced speech has a low volume but a high ZCR

Mel-Frequency Cepstral Coefficients (MFCC)

- First five coefficients provide the best genre classification performance



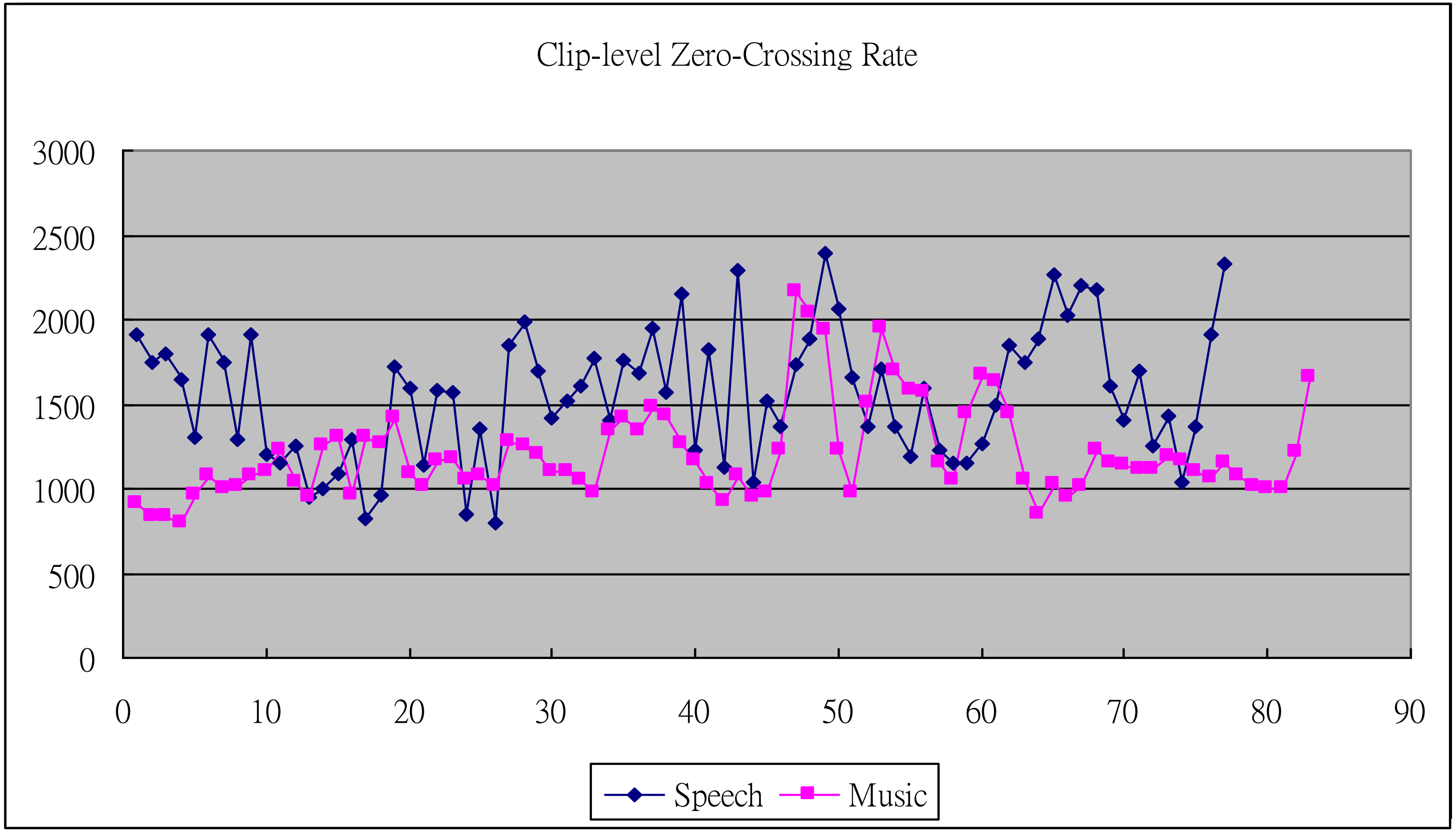
$$X_a[k] = \sum_{n=0}^{N-1} x[n] e^{-j2\pi nk/N}, \qquad 0 \le k < N$$

$$S[m] = \ln\left[\sum_{k=0}^{N-1} |X_a[k]|^2 H_m[k]\right], \qquad 0 < m \le M$$

$$c[n] = \sum_{m=0}^{M-1} S[m]\cos(\pi n(m-1/2)/M), \qquad 0 \le n < M$$

M: the number of filters
N: the size of the FFT

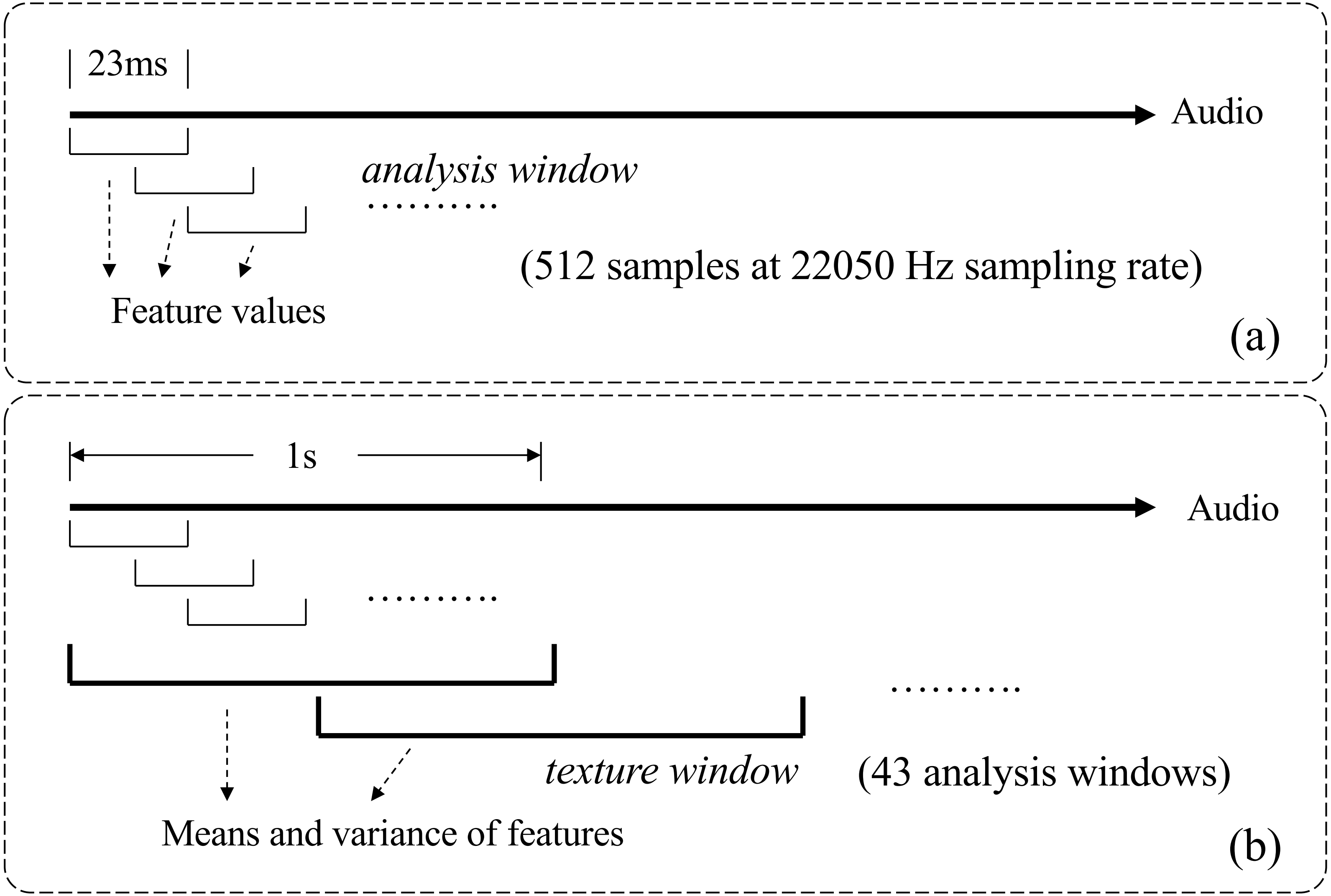
Examples of Audio Features



Analysis and Texture Window (1/2)

- For short-time audio analysis, small audio segments are processed (*analysis window*).
- To capture the long term nature of sound “texture”, means and variances of features over a number of *analysis windows* are calculated (*texture windows*).
- For each texture window, multidimensional Gaussian distribution of features are estimated.

Analysis and Texture Window (2/2)



Low-Energy Feature

- Based on the texture window
- The percentage of analysis windows that have less energy than the average energy across the texture window.
- Ex: vocal music with silences have large low-energy value

Rhythmic Content Features

- Characteristics: the regularity of the rhythm, the relation of the main beat to the subbeats, and the relative strength of subbeats to the main beat
- Steps of a common automatic beat detector
  - 1. Filterbank decomposition
  - 2. Envelop extraction
  - 3. Periodicity detection algorithm used to detect the lag at which the signal's envelope is most similar to itself
- Similar to pitch detection but with larger periods: approximately 0.5 to 1.5 s for beat vs. 2 ms to 50 ms for pitch

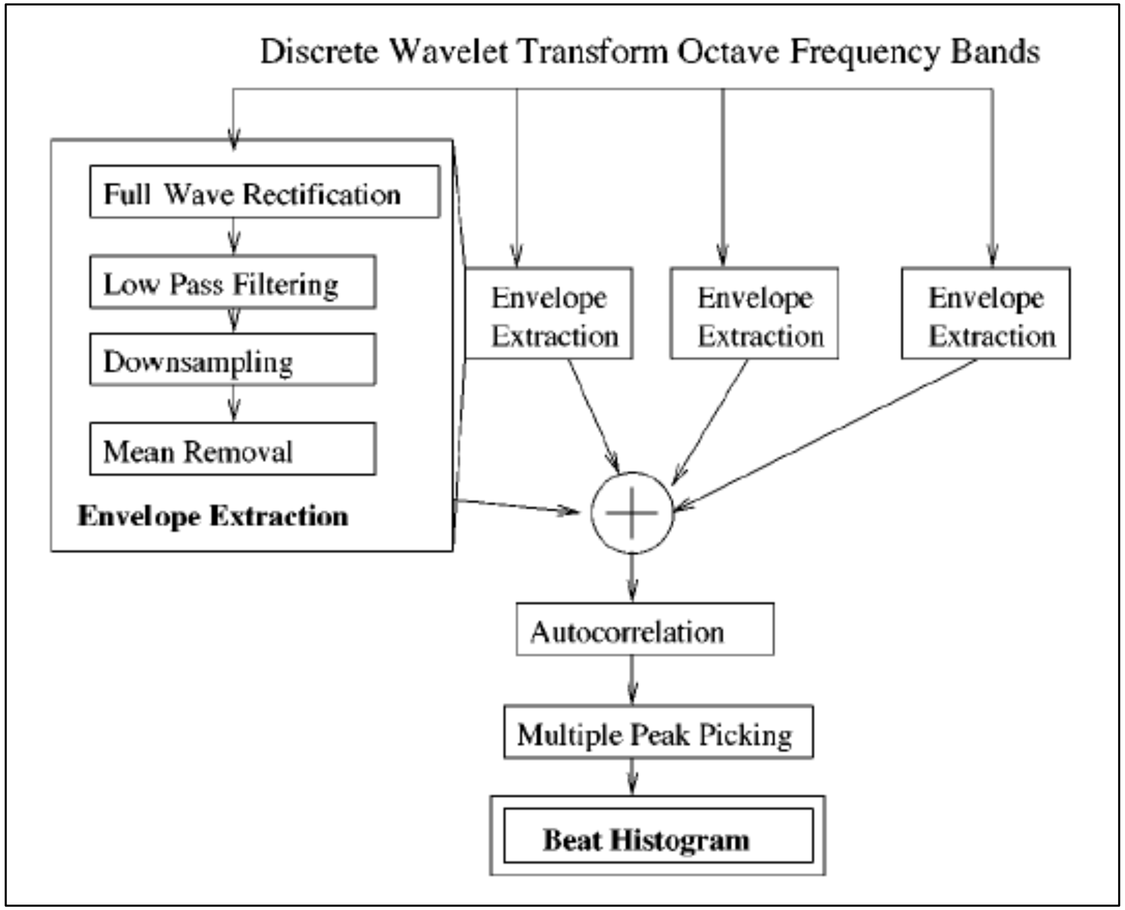
Rhythmic Content Features

- Based on discrete wavelet transform (DWT)
  - Overcome the resolution problems (people percept differently in different freq. bands)
  - The DWT can be viewed as a computationally efficient way to calculate an octave decomposition of the signal in frequency.
  - DAUB4 filters are used.
- Find the rhythmic structure: detect the most salient periodicities of the signal

Rhythmic Content Features

- Beat detection flowchart

Beat: the sequence of equally spaced phenomenal impulses which define a tempo for the music



Octave

- 在數理上，每一個八度音程(Octave)正好對應於不同的振動模式，而兩個八度音程差的音在頻率上正好差上兩倍。例如：在第0個八度的La(記為A0)頻率為27.5 Hertz，則第1個八度的La(記為A1)頻率即為27.5*2=55.0 Hertz。在這每一個八度的音程中，又可再將其等分為12個頻率差相近的音，這分別對應於【C Db D Eb E F Gb G Ab A Bb B】，這樣的等分法就是所謂的十二平均律(Twelve-Tone Scale)。這當中每一個音符所對應的頻率，都可以藉由數學的方程式準確的算出

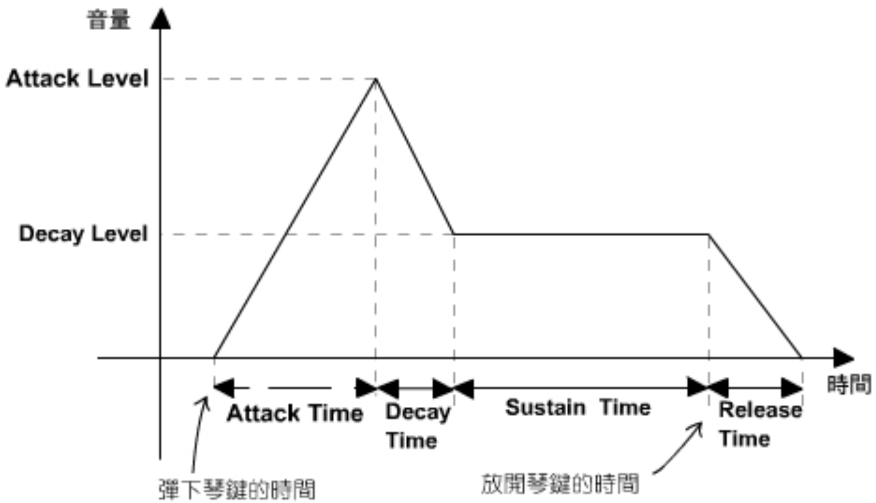
Octave and Semi-tone

- There are 12 semitones in one octave, so a tone of frequency f_1 is said to be a semitone above a tone with frequency f_2 iff

  $f_1 = 2^{1/12} f_2 = 1.05946 f_2$

Envelope

- 將一種音色波形的大致輪廓描繪出來，就可以表示出該音色在音量變化上的特性，而這個輪廓就稱為Envelope(波封)
- 一個波封可以用4種參數來描述，分別是Attack(起音)、Decay(衰減)、Sustain(延持)、與Release(釋音)，這四者也就是一般稱的"ADSR"。



Envelop Extraction

- Full Wave Rectification

$$y[n] = |x[n]|$$

To extract the temporal envelope of the signal rather than the time domain signal itself

- Low-Pass Filtering (smoothing)

$$y[n] = (1-\alpha)x[n] + \alpha y[n-1], \quad \alpha = 0.99$$

To smooth the envelope

- Downsampling

$$y[n] = x[kn] \qquad k=16$$

Reduce the computation time

- Mean Removal

$$y[n] = x[n] - E[x[n]]$$

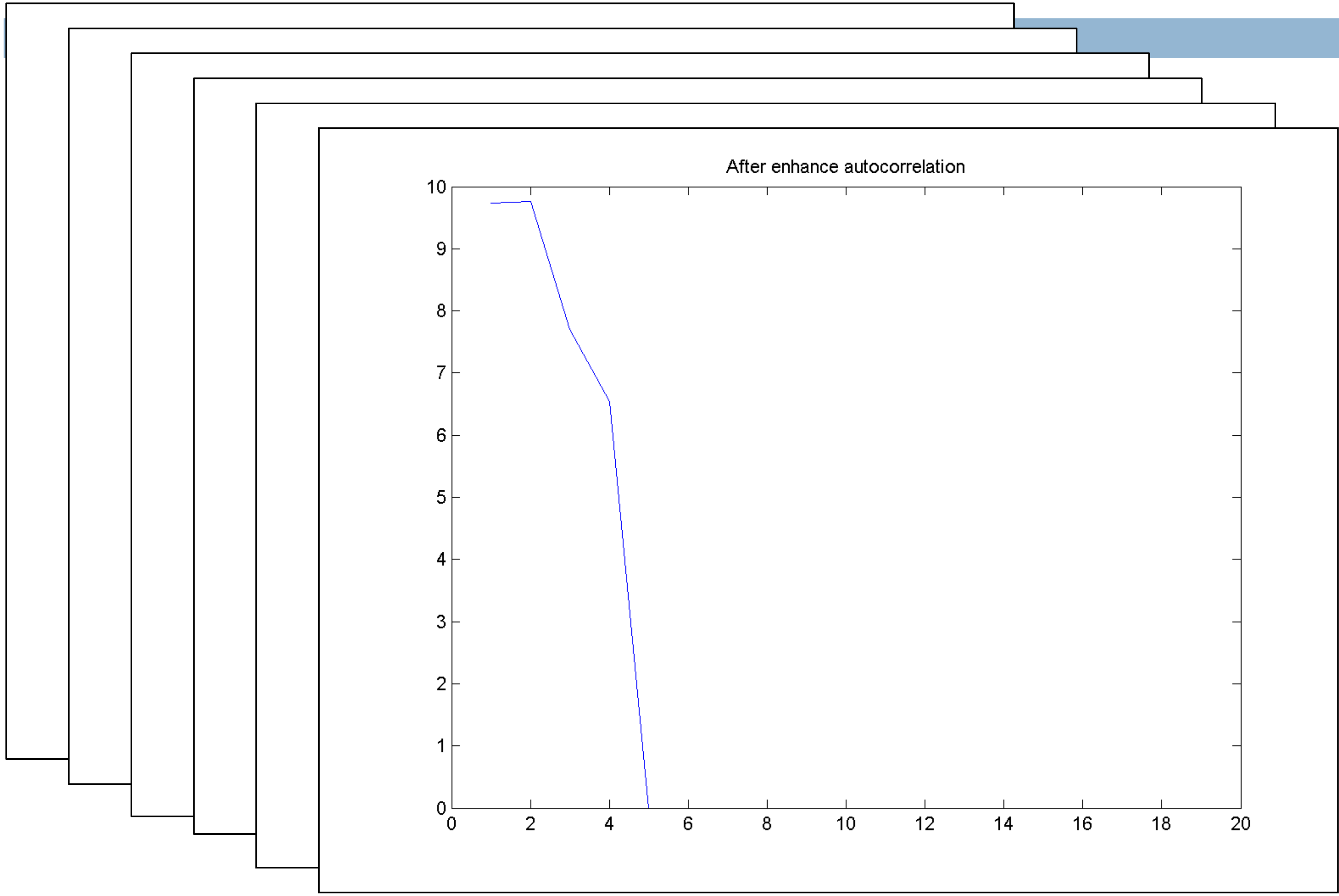
To make the signal centered to zero for the autocorrelation stage

Enhanced Autocorrelation

$$y[k] = \frac{1}{N} \sum_n x[n]x[n-k]$$

- The peaks of the autocorrelation function correspond to the time lags where the signal is most similar to itself
- The time lags correspond to beat periodicities

Example

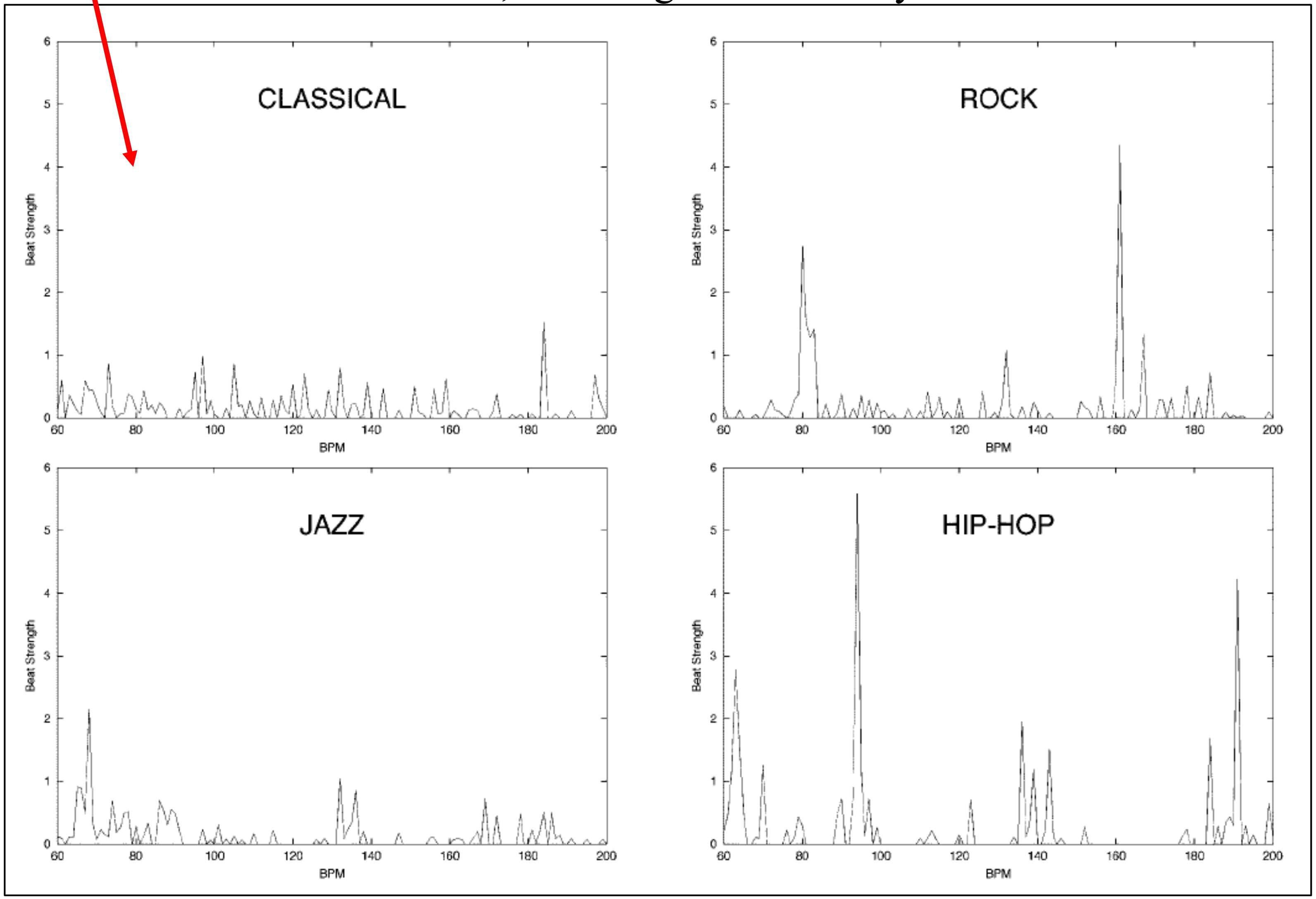

After enhance autocorrelation
10
9
8
7
6
5
4
3
2
1
0
0
2
4
6
8
10
12
14
16
18
20

Peak Detection and Histogram Calculation

- The first three peaks of the enhanced autocorrelation function are selected and added to a beat histogram (BH).
- The bins of BH correspond to beats-per-minute (bpm) from 40 to 200 bpm.
- For each peak, the peak amplitude is added to the histogram.
  - Peaks having high amplitude (where the signal is highly similar) are weighted more strongly

Beat Histogram

Multiple instruments of the orchestra, no strong self-similarity



Beat Histogram Features

- A0, A1: relative amplitude (divided by the sum of amplitudes) of the first and second histogram peak
- RA: ratio of the amplitude of the second peak divided by the amplitude of the first peak
- P1, P2: period of the first and second peaks in bpm
- SUM: overall sum of the histogram (indication of beat strength)

Introduction of Pitch

- Pitch (音高): 構成樂音的最基本要素在於音高，也就是聲音的頻率。
- 在樂理上，樂音音符可分為七個基本音，即【Do Re Me Fa Sol La Si】，以美式的符號則記為【C D E F G A B】而第八個音則稱為高八度的Do。

Pitch Content Feature

- The signal is decomposed into two frequency bands (below and above 1000 Hz)
- Envelope extraction is performed for each frequency band.
- The envelopes are summed and an enhanced autocorrelation function is computed.
- The prominent peaks correspond to the main pitches for that short segment of sound.

Beat and Pitch Detection

- The process of beat detection resembles pitch detection with larger periods.
- For beat detection, a window of 65536 samples at 22050 Hz is used.
- For pitch detection, a window of 512 samples is used.

Autocorrelation: $y[k] = \dfrac{1}{N} \sum_n x[n]x[n-k]$

different range of k

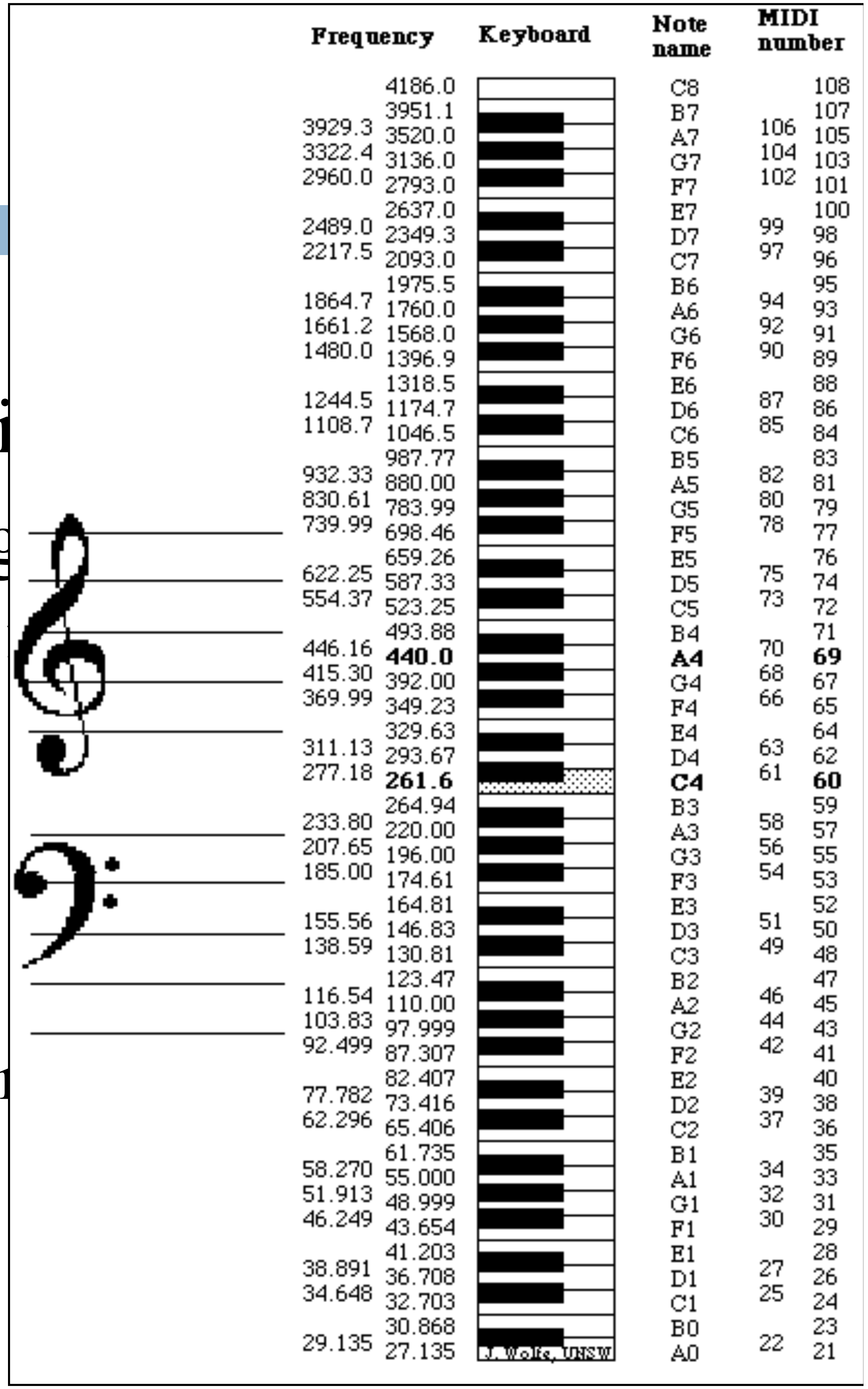
Pitch Histogram

- For each analysis window, the are accumulated into a pitch hi
- The frequencies corresponding peak are converted to musical

$$n = 12 \times \log_2 \frac{f}{440} + 69$$

f is the frequency in Hertz
n is the histogram bin (MIDI note
http://www.phys.unsw.edu.au/~jw/notes.html

69
70
semitone



Folded and Unfolded PH

- In the folded case (FPH)

  $$c = n \bmod 12$$

  c is the folded histogram bin
  n is the unfolded histogram bin

- The folded version (FPH) contains information regarding the pitch classes or harmonic content of the music. The unfolded version (UPH) contains information about the pitch range of the piece.

Modified FPH

- The FPH is mapped to a circle of fifths histogram so that adjacent histogram bins are spaced a fifth apart rather than a semitone

$$c' = (7 \times c) \bmod 12$$

五度音程：三個全音加上一個半音的距離
G→全音→A→全音→B→半音→C→全音→D

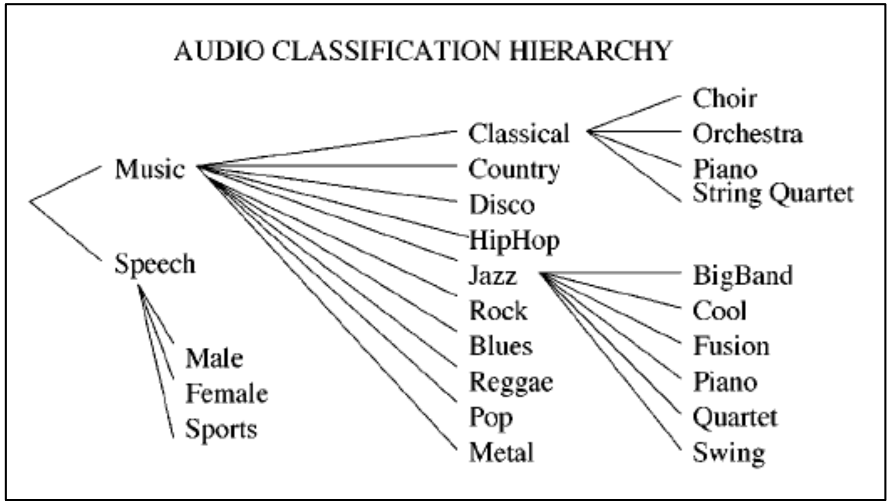
- The distances between adjacent bins after mapping are better suited for expressing tonal music relations
- Jazz or classical music tend to have a higher degree of pitch change than rock or pop music.

Pitch Histogram Features

- FA0: amplitude of maximum peak of the folded histogram.
- UP0, FP0: period of the maximum peak of the unfolded and folded histograms
- IPO1: pitch interval between the two most prominent of the folded histogram (main tonal interval relation)
- SUM: the overall sum of the histogram

Evaluation

- Classification
  - Simple Gaussian classifier
  - Gaussian mixture model
  - K-nearest neighbor classifier
- Datasets
  - 20 musical genres and 3 speech genres
  - 100 excerpts each with 30 sec
  - Taken from radio, CD, and mp3. The files were stored as 22050 Hz, 16-bit, mono audio files.



Experiments

- Use a single-vector to represent the whole audio file.
- The vector consists of timbral texture features (9(FFT)+10(MFCC)=19-dim), rhythmic content features (6-dim), and the pitch content features (5-dim)
- 10-fold cross validation (90% training and 10% testing each time)

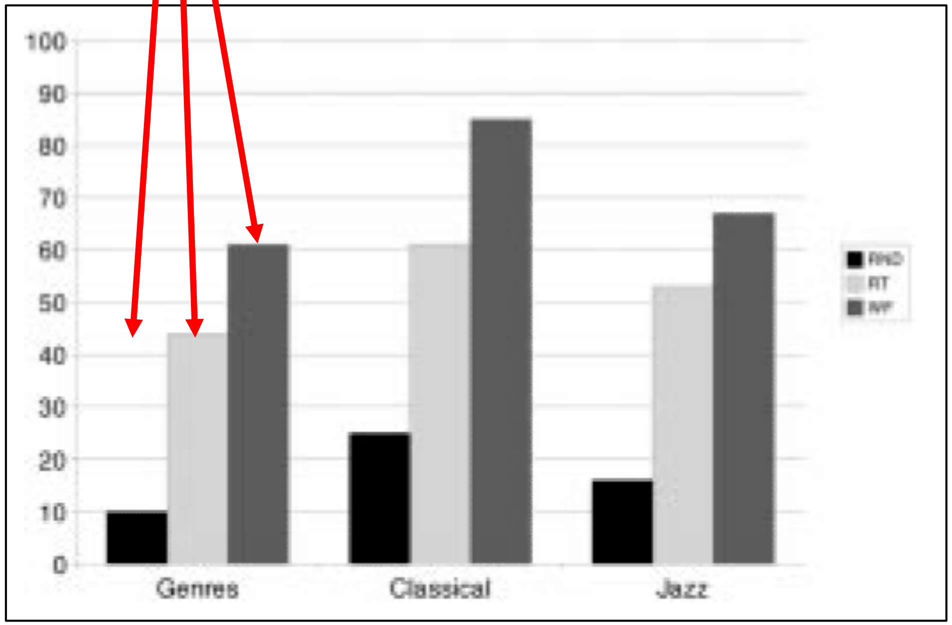
Results

- RT GS: for real-time classification per frame using only timbral texture feature
- GS: simple Gaussian

Random, RT GS, and GMM(3)

TABLE I
CLASSIFICATION ACCURACY MEAN AND STANDARD DEVIATION

	Genres(10)	Classical(4)	Jazz(6)
Random	10	25	16
RT GS	44 ± 2	61 ± 3	53 ± 4
GS	59 ± 4	77 ± 6	61 ± 8
GMM(2)	60 ± 4	81 ± 5	66 ± 7
GMM(3)	61 ± 4	88 ± 4	68 ± 7
GMM(4)	61 ± 4	88 ± 5	62 ± 6
GMM(5)	61 ± 4	88 ± 5	59 ± 6
KNN(1)	59 ± 4	77 ± 7	57 ± 6
KNN(3)	60 ± 4	78 ± 6	58 ± 7
KNN(5)	56 ± 3	70 ± 6	56 ± 6



Other Classification Results

- The STFT-based feature set is used for the music/speech classification
  - 86% accuracy
- The MFCC-based feature set is used for the speech classification
  - 74% accuracy

Detailed Performance

TABLE II
GENRE CONFUSION MATRIX

	cl	co	di	hi	ja	ro	bl	re	po	me
cl	**69**	0	0	0	1	0	0	0	0	0
co	0	**53**	2	0	5	8	6	4	2	0
di	0	8	**52**	11	0	13	14	5	9	6
hi	0	3	18	**64**	1	6	3	26	7	6
ja	26	4	0	0	**75**	8	7	1	2	1
ro	5	13	4	1	9	**40**	14	1	7	33
bl	0	7	0	1	3	4	**43**	1	0	0
re	0	9	10	18	2	12	11	**59**	7	1
po	0	2	14	5	3	5	0	3	**66**	0
me	0	1	0	1	0	4	2	0	0	**53**

cl: classical
co: country
di: disco
hi: hiphop
ja: jazz
ro: rock
bl: blues
re: reggae
po: pop
me: mental

26% of classical music is wrongly classified as jazz music

- The matrix shows that the misclassifications of the system are similar to what a human would do.

Rock music has worst accuracy because of its broad nature

Performance on Classical and Jazz

TABLE III
JAZZ CONFUSION MATRIX

	BBand	Cool	Fus.	Piano	4tet	Swing
BBand	**42**	2	1	0	6	1
Cool	21	**67**	5	4	23	10
Fus.	28	16	**88**	0	38	22
Piano	1	0	0	**80**	0	0
4tet	4	5	2	0	**19**	5
Swing	4	10	4	16	14	**62**

BBand: bigband
Cool: cool
Fus.: fusion
Piano: piano
4tet: quartet (四重奏)
Swing: swing

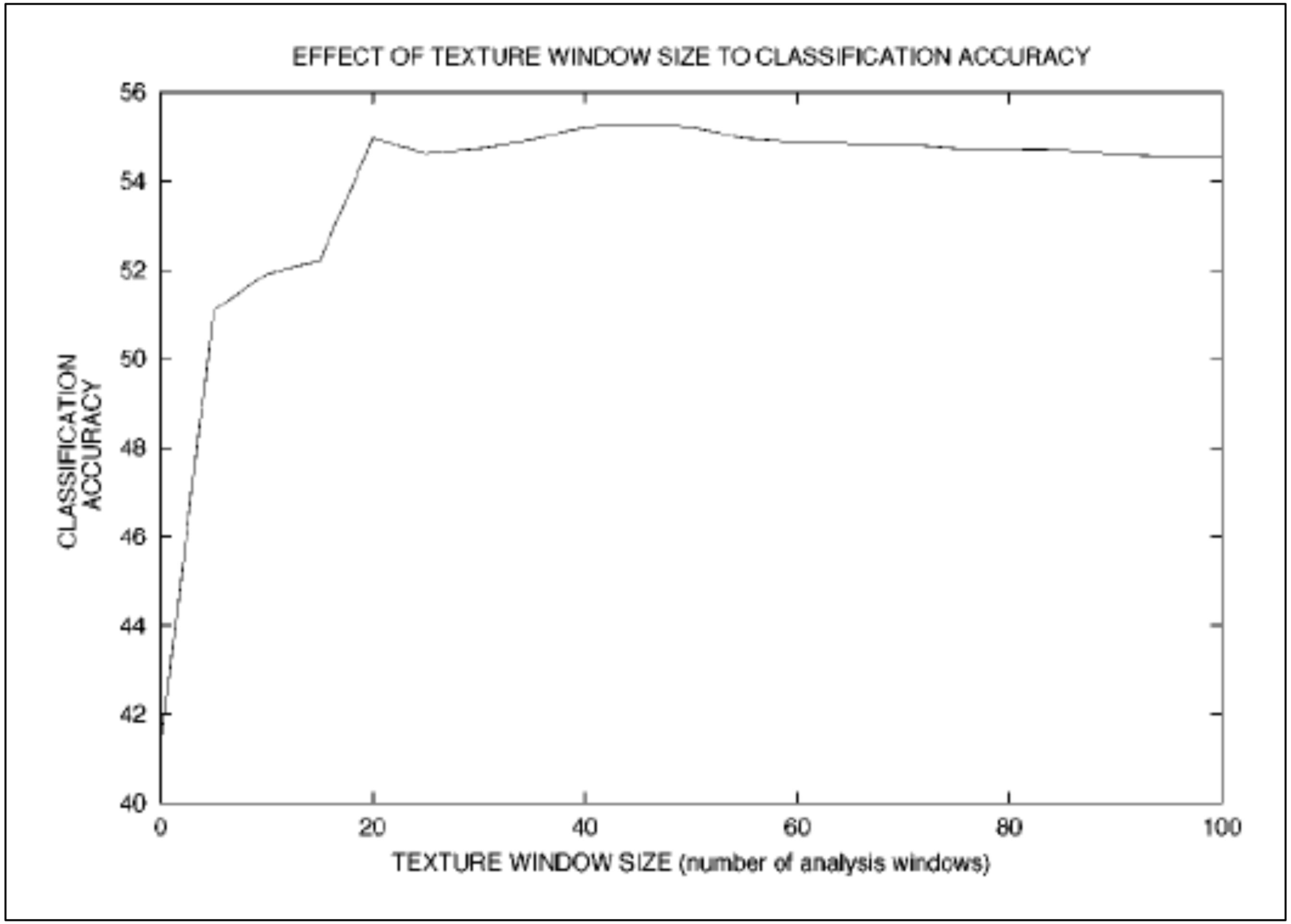
TABLE IV
CLASSICAL CONFUSION MATRIX

	Choir	Orch.	Piano	Str.4tet
Choir	**99**	7	7	3
Orch.	0	**58**	2	7
Piano	0	9	**86**	4
Str.4tet	1	26	5	**86**

Choir: choir
Orch.: orchestra
Piano: piano
Str.4tet: String Quarter (弦樂四重奏)

Importance of Texture Window Size

- 40 analysis windows was chosen



Importance of Individual Feature Sets

- Pitch histogram features and beat histogram features perform worse than the timbral-texture features (STFT, MFCC)

TABLE V
INDIVIDUAL FEATURE SET IMPORTANCE

	Genres	Classical	Jazz
RND	10	25	16
PHF(5)	23	40	26
BHF(6)	28	39	31
STFT(9)	45	78	58
MFCC(10)	47	61	56
FULL(30)	59	77	61

The rhythmic and pitch content feature sets seem to play a less important role in the classical and jazz dataset classification

It's possible to design genre-specific feature sets.

Human Performance for Genre Classification

- Ten genres used in previous study: blues, country, classical, dance, jazz, latin, pop, R&B, rap, and rock
- 70% correct after listening to 3 sec
- Although direct comparison of these results is not possible, it's clear that the automatic performance is not far away from the human performance.

Conclusion

- Three feature sets are proposed: timbral texture, rhythmic content, and pitch content features
- 61% accuracy has been achieved
- Possible improvements:
  - Information from melody and singer voice
  - Expand the genre hierarchy both in width and depth
  - More exploration of pitch content features