



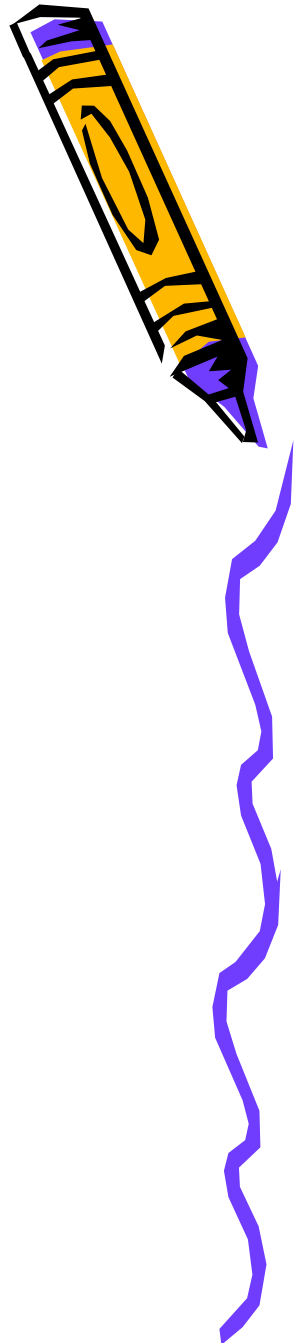
**Automatic Mood  
Detection from  
Acoustic Music Data**

Dan Liu, Lie Lu, Hong-Jiang Zhang

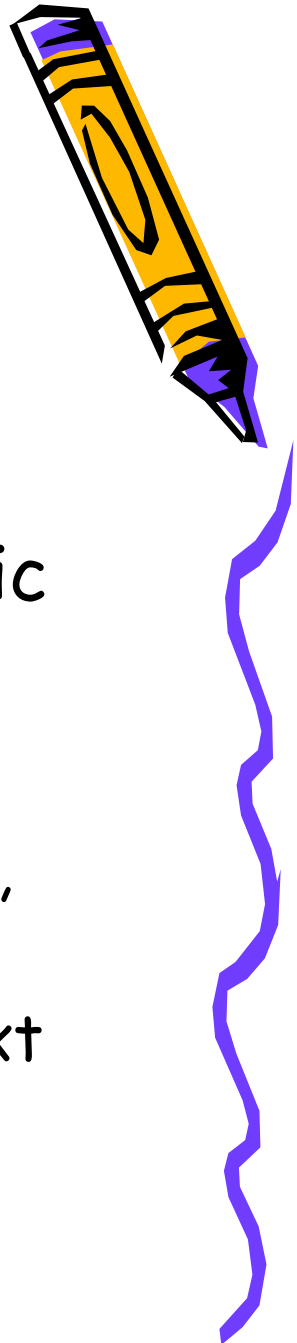
Contact: [dliu@Cogsci.ucsd.edu](mailto:dliu@Cogsci.ucsd.edu)

# Outline

- Introduction
- Feature Extraction
- Mood Detection
- Mood Tracking
- Experiment
- Conclusion



# 1. Introduction

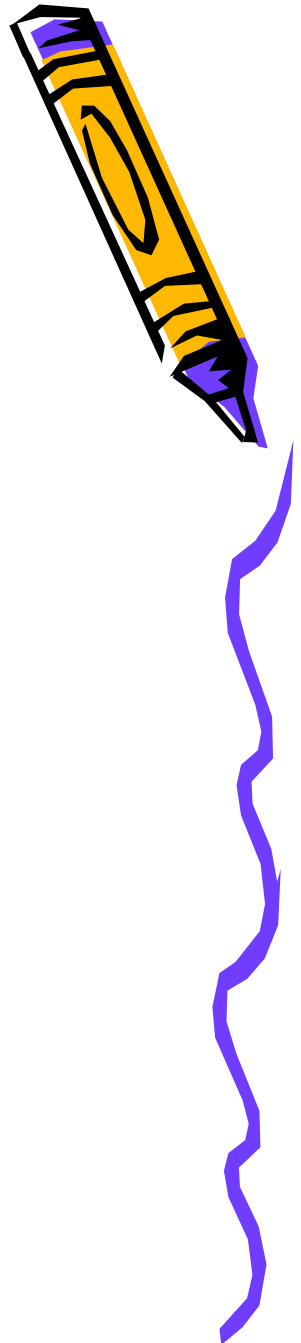


- Music Mood
  - A semantic metadata to archive music from database
  - Objective or Subjective
    - Depend on many factors such as culture, education, experience...
    - Consistent within a given cultural context



# 1. Introduction

- Relevant works
  - Concentrate on MIDI or symbolic representations
  - Use various mood descriptors



# 1. Introduction

- Music Mood Taxonomy
  - Hevner's adjective checklist (1935)

- Descriptors are ambiguous
- Difficult for computational modeling

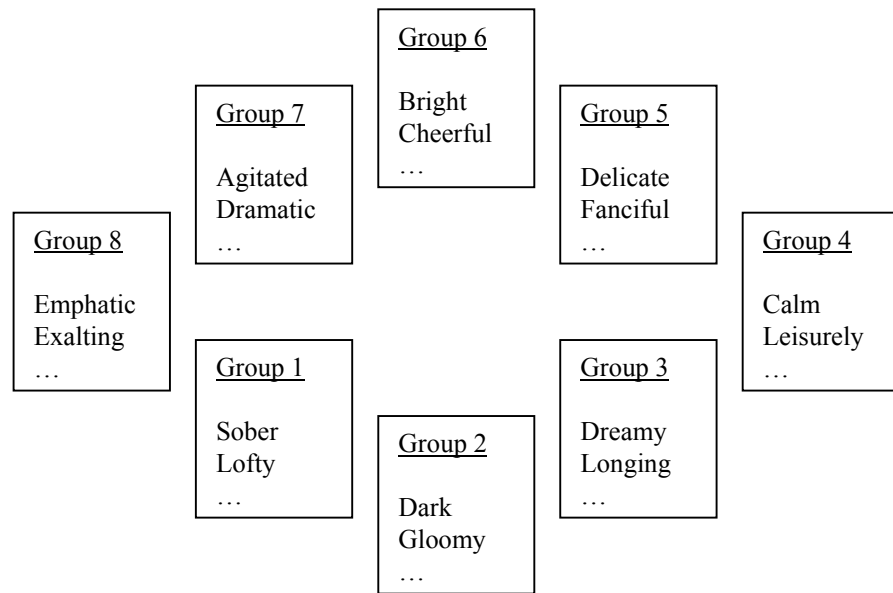


Figure 1: Hevner's adjective checklist



# 1. Introduction

- Music Mood Taxonomy
  - Thayer's two-dimensional model (1990)
- Descriptors are explicit and discriminatable
- Easier for computational modeling

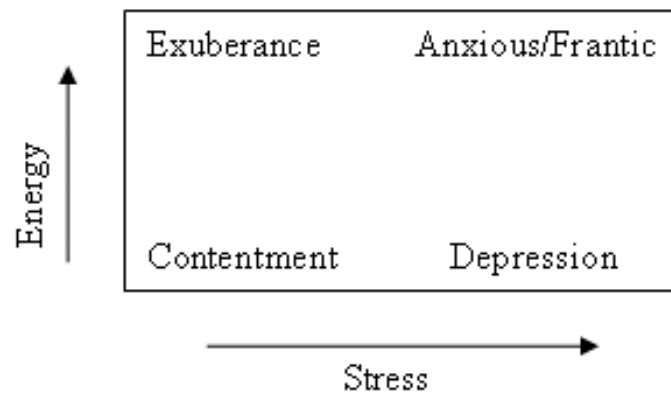
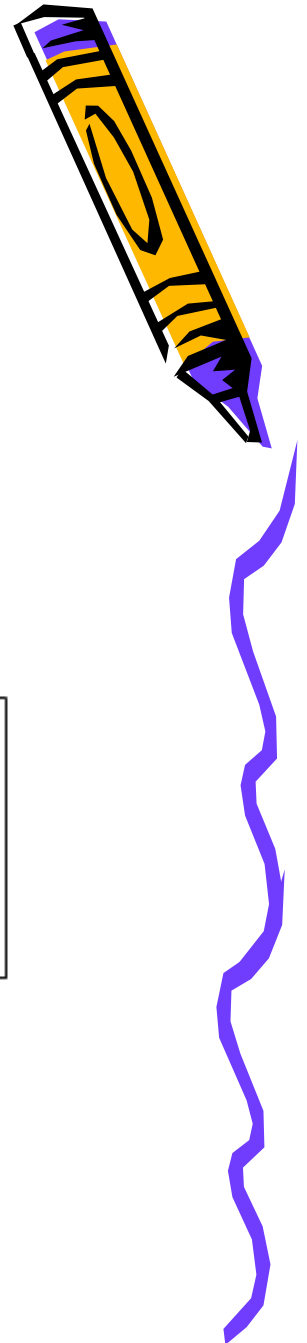
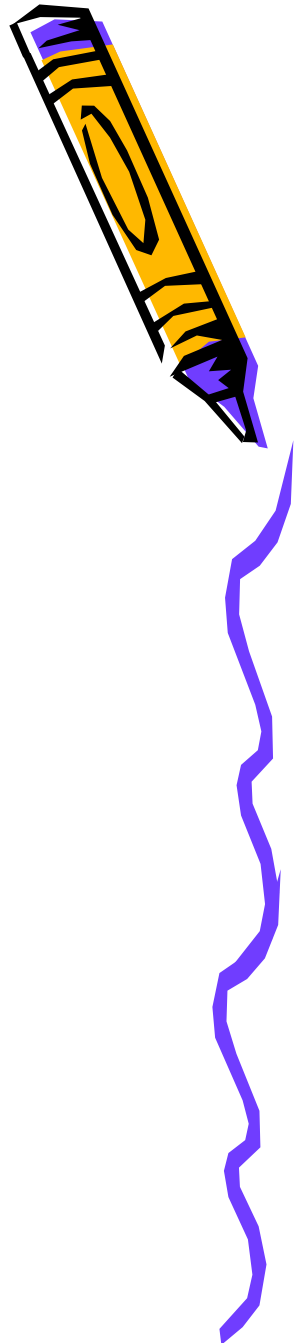


Figure 2: Thayer's model of mood



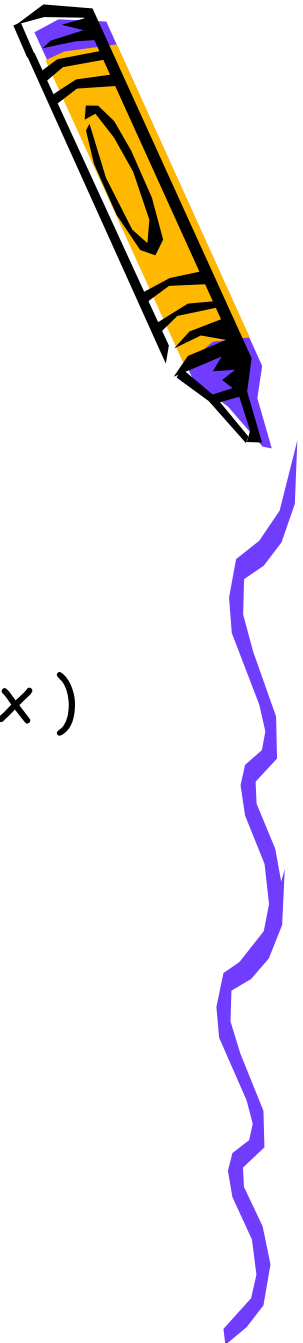
## 2. Feature Extraction

- Relevant Music Features
  - Intensity Features
  - Timbre Features
  - Rhythm Features
  - Mode Features (not available)



## 2. Feature Extraction

- Timbre Features
  - Spectral Shape Features  
(centroid, bandwidth, roll off, spectral flux )
  - Spectral Contrast Features
    - Sub-band Peak
    - Sub-band Valley
    - Sub-band Average





## 2. Feature Extraction



- Intensity Features
  - Sub-band Intensity: root mean-square (RMS) in each sub-band
  - Total Intensity: sum of sub-band Intensity



# 2. Feature Extraction

- Rhythm Features

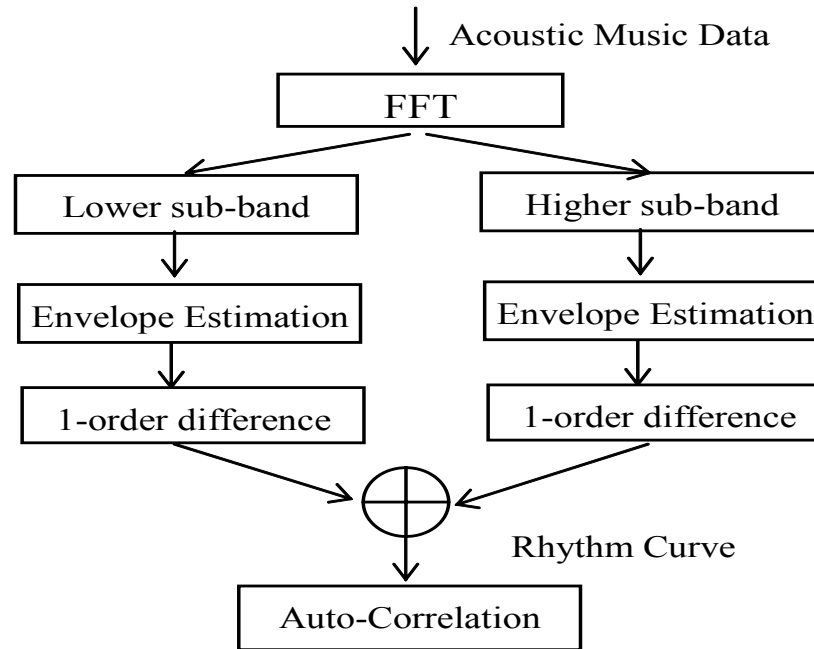


Figure 3: Rhythm features extraction



## 2. Feature Extraction

- Rhythm Features
  - Average Strength: average strength of bass instrumental onsets.
  - Average Correlation Peak: average of the maximum three peaks in the auto-correlation curve.
  - Average Tempo: the common divisor of the peaks of the auto-correlation curve.



# 3. Mood Detection

- Hierarchical Framework

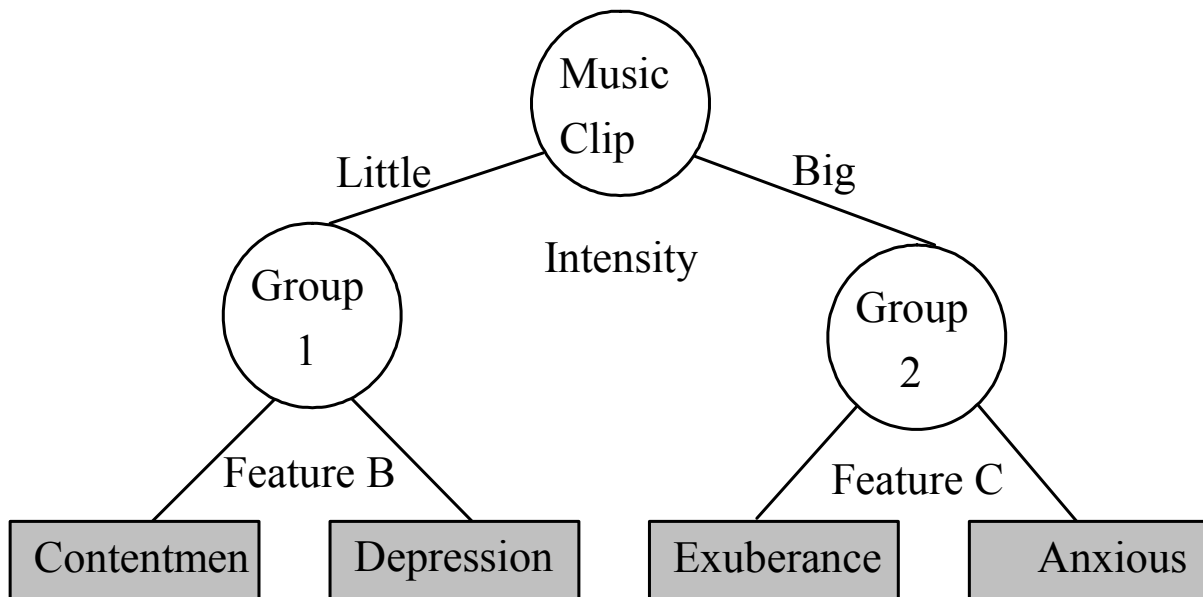


Figure 4: The hierarchical mood detection framework



# 3. Mood Detection

- Hierarchical Process

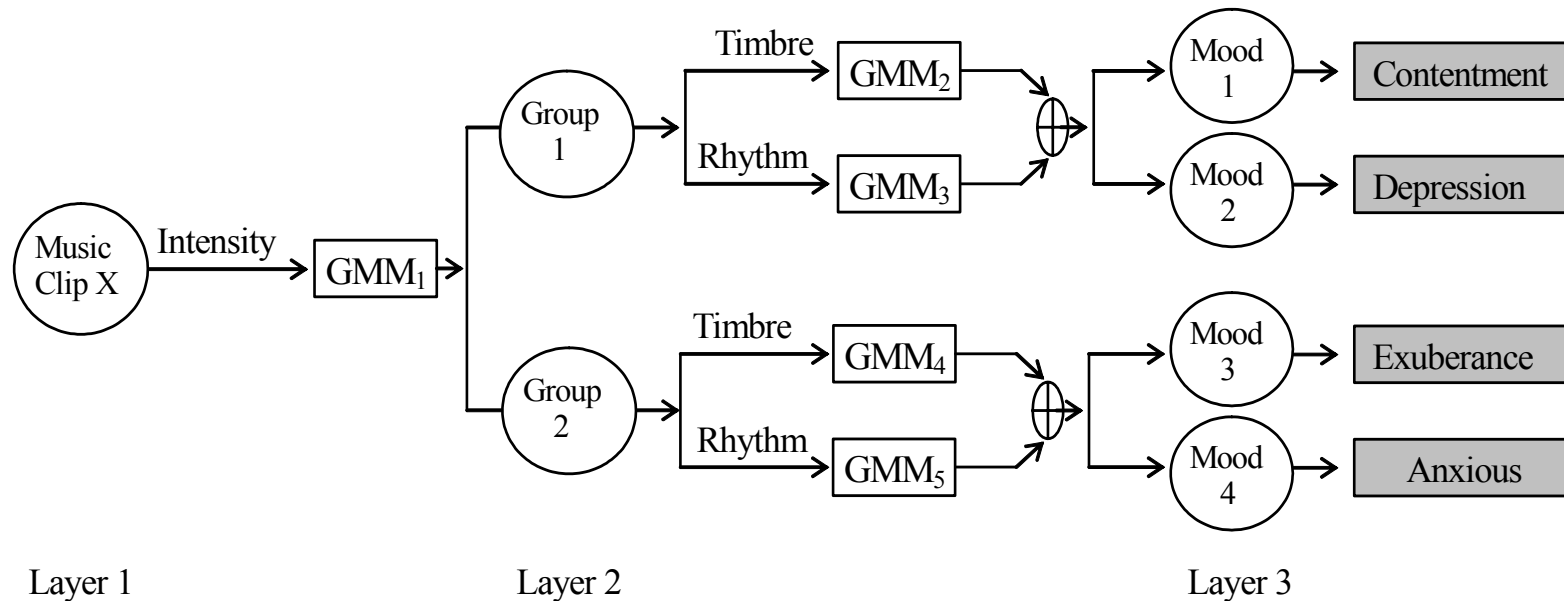


Figure 5: The hierarchical Mood detection process



# 3. Mood Detection

## Step1. Group Classification

$$\frac{P(G_1 | I)}{P(G_2 | I)} \begin{cases} \geq 1, & \text{Select } G_1 \\ < 1, & \text{Select } G_2 \end{cases}$$

## Step 2. Mood classification in each group

$$P(M_j | G_1, T, R) = \lambda_1 \times P(M_j | T) + (1 - \lambda_1) \times P(M_j | R) \quad j = 1, 2$$

$$P(M_j | G_2, T, R) = \lambda_2 \times P(M_j | T) + (1 - \lambda_2) \times P(M_j | R) \quad j = 3, 4$$



# 4. Mood Tracking



- Why we need to track the mood
  - Mood is changeable in music
- How to track the changeable mood
  - Segmentation based on music features (timbre and intensity)
  - Mood detection in each segment



# 4. Mood Tracking

- Segmentation Procedure

- 1) Compute the distance between two contiguous windows based on timbre and intensity features

$$D = \frac{1}{2} \text{tr} [(C_i - C_j)(C_j^{-1} - C_i^{-1})]$$

- 2) Compute confidence of being a boundary

$$\text{Conf}_I = \frac{1}{A_I} \exp\left(\frac{D_I - \mu_I}{\sigma_I}\right), \quad \text{Conf}_T = \frac{1}{A_T} \exp\left(\frac{D_T - \mu_T}{\sigma_T}\right)$$

$$\text{Conf} = \alpha \times \text{Conf}_I + (1 - \alpha) \times \text{Conf}_T$$





# 4. Mood Tracking

- Segmentation Procedure

## 3) Detect potential boundaries

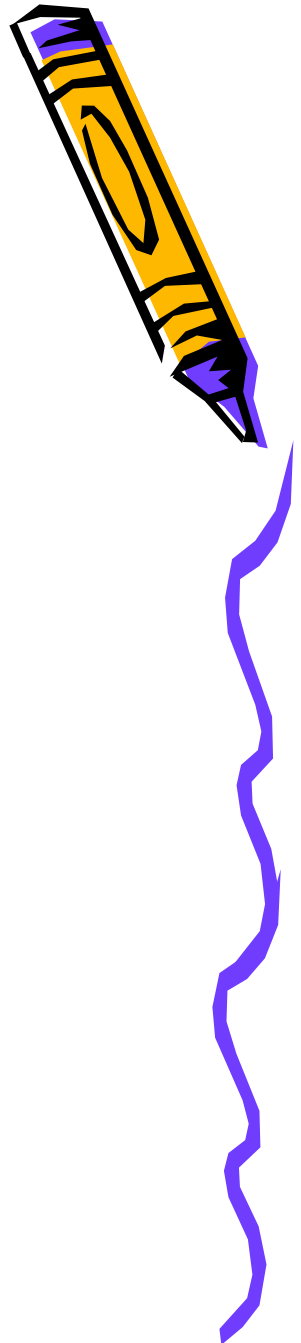
I.  $Conf(i, i + 1) > Conf(i + 1, i + 2)$

II.  $Conf(i, i + 1) > Conf(i - 1, i)$

III.  $Conf(i, i + 1) > Th_i$

$$Th_i = \alpha \times \frac{1}{2 \times N} \sum_{n=-N}^N Conf(i - n - 1, i - n)$$

## 4) Refine potential boundaries



# 5. Experiment

- Mood Detection on Music Clips
  - Database
    - 250 pieces of music, mainly in the classical period and romantic period
    - 200 representative music clips of 20 seconds long for each of the four mood clusters
  - Experiment
    - Cross-validation evaluation with 25% used for testing and 75% for training.
    - Iterated with different random partitions and the results are averaged



# 5. Experiment

- Experiment results on hierarchical framework

(1) Optimal average accuracy achieved when

$$\lambda_1(\text{weighting of Timbre in Group 1}) = 0.8$$

$$\lambda_2(\text{weighting of Timbre in Group 1}) = 0.4$$

Timbre features are more important to classify Contentment and Depression in Group 1, and rhythm features are more important to discriminate Exuberance and Anxious in Group 2.



# 5. Experiment

- Experiment result on hierarchical framework

(2) Only 1.6% music in Group 1 (Contentment and Depression) is classified into Group 2 (Exuberance and Anxious), while only 0.4% music in Group 2 is classified into Group 1

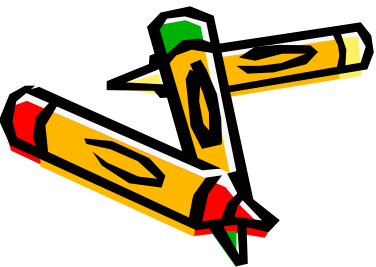
This result confirms the good performance of intensity features in discriminating the two groups of mood clusters.



# 5. Experiment

- Comparison of hierarchical framework and non-hierarchical framework ([See Results](#))
  - Overall classification accuracy for hierarchical framework is up to 86.3%, about 5.7% better than the non-hierarchical framework, and its standard deviation decreases from 10.7% to 5.2%.
  - Classification accuracies for all of the four clusters are improved by using hierarchical framework, especially for Exuberance (85.5% improved from 64.7%).

Hierarchical framework has a better performance than its non-hierarchical counterpart, by using the most efficient features for different mood clusters.



# 5. Experiment



- Mood Tracking
  - Haydn's "Serenade" : constantly Contentment
  - Second movement of Beethoven's "Symphony No. 3": mainly Depression
  - Tchaikovsky's "1812 Overture": changeable

Mood tracking performance based on segmentation is better than that of detecting mood every 20 seconds.

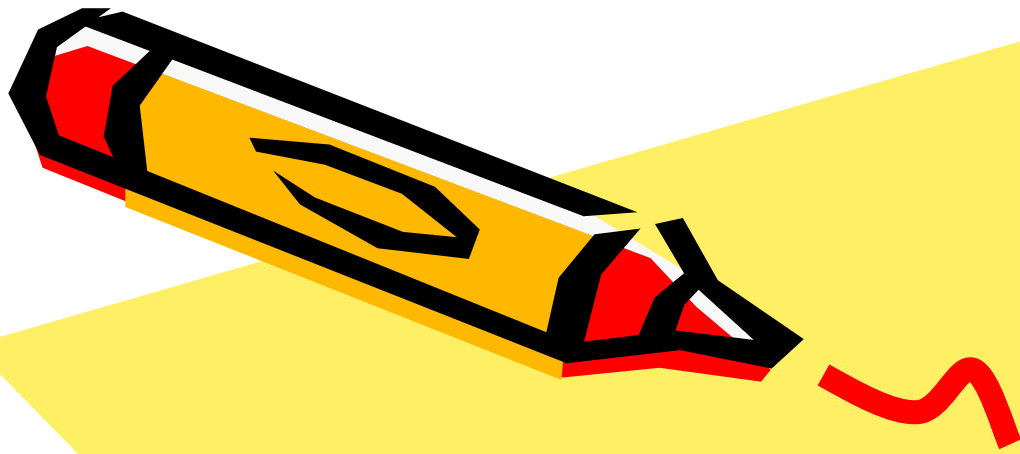


# 6. Conclusion



- Thayer's model of mood is adopted for mood taxonomy
- Intensity, timbre and rhythm feature sets are extracted directly from acoustic data.
- A hierarchical framework is developed to detect the mood in a music clip.
- A segmentation scheme is presented to track the mood in a whole piece of music.





Thank You !

10/27/2003



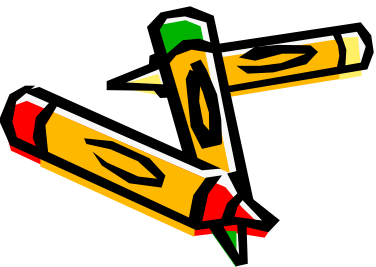


Table 1: Mood detection confusion matrix based on hierarchical framework

	<b>Contentment</b>	<b>Depression</b>	<b>Exuberance</b>	<b>Anxious</b>
<b>Contentment</b>	<b>76.6 ± 7.6</b>	21.8 ± 7.2	0.5 ± 0.8	1.2 ± 1.2
<b>Depression</b>	4.0 ± 3.5	<b>94.5 ± 3.4</b>	0 ± 0	1.5 ± 2.5
<b>Exuberance</b>	0 ± 0	0.8 ± 1.3	<b>85.5 ± 3.2</b>	13.7 ± 4.8
<b>Anxious</b>	0 ± 0	0 ± 0	11.5 ± 6.7	<b>88.5 ± 6.7</b>

Table 2: Mood detection confusion matrix based on non-hierarchical framework

	<b>Contentment</b>	<b>Depression</b>	<b>Exuberance</b>	<b>Anxious</b>
<b>Contentment</b>	<b>75.0 ± 11.8</b>	25.0 ± 11.8	0 ± 0	0 ± 0
<b>Depression</b>	5.8 ± 2.6	<b>94.2 ± 2.6</b>	0 ± 0	0 ± 0
<b>Exuberance</b>	1.5 ± 2.6	0.7 ± 1.3	<b>64.7 ± 20.5</b>	33.0 ± 18.3
<b>Anxious</b>	0 ± 0	0 ± 0	11.5 ± 6.7	<b>88.3 ± 7.9</b>



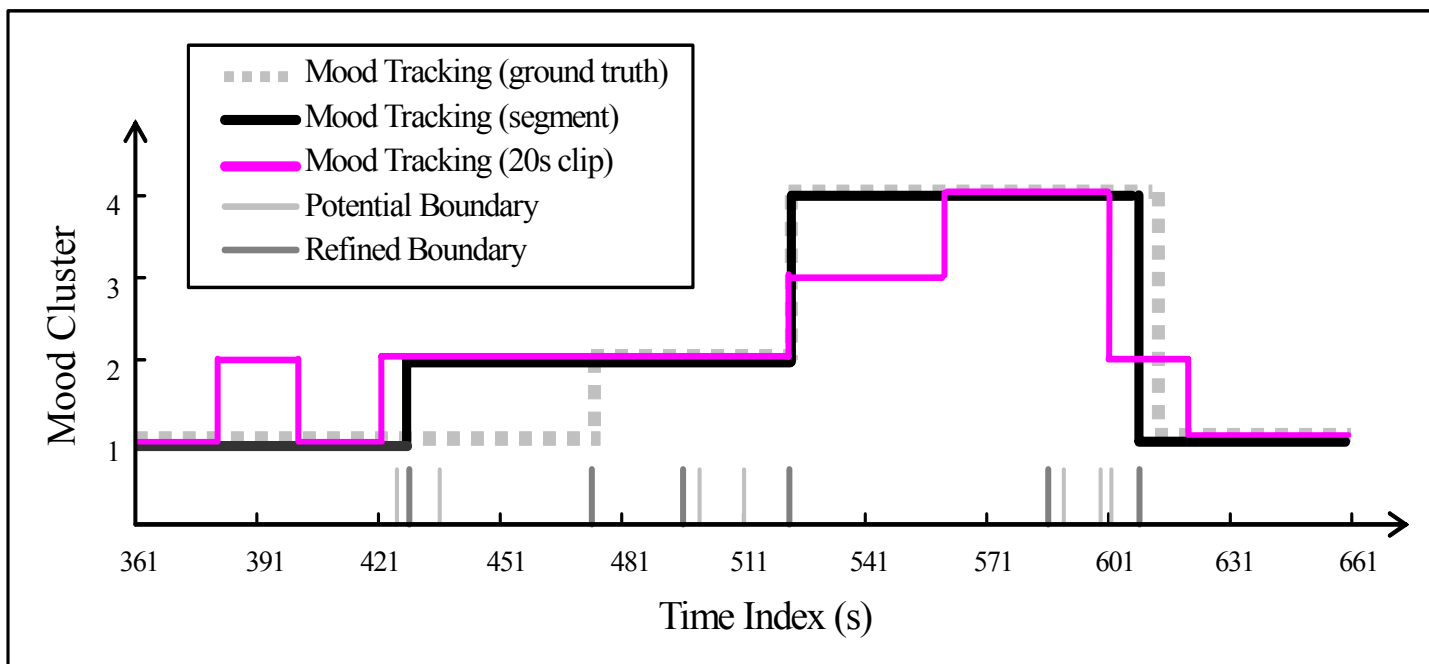


Figure 6: Mood tracking results on a part of "1812 Overture" (from 361s - 661s)

