浙江大学计算机学院
数字媒体与网络技术

Digital Asset Management
数字媒体资源管理

6. Introduction to Digital Media Retrieval

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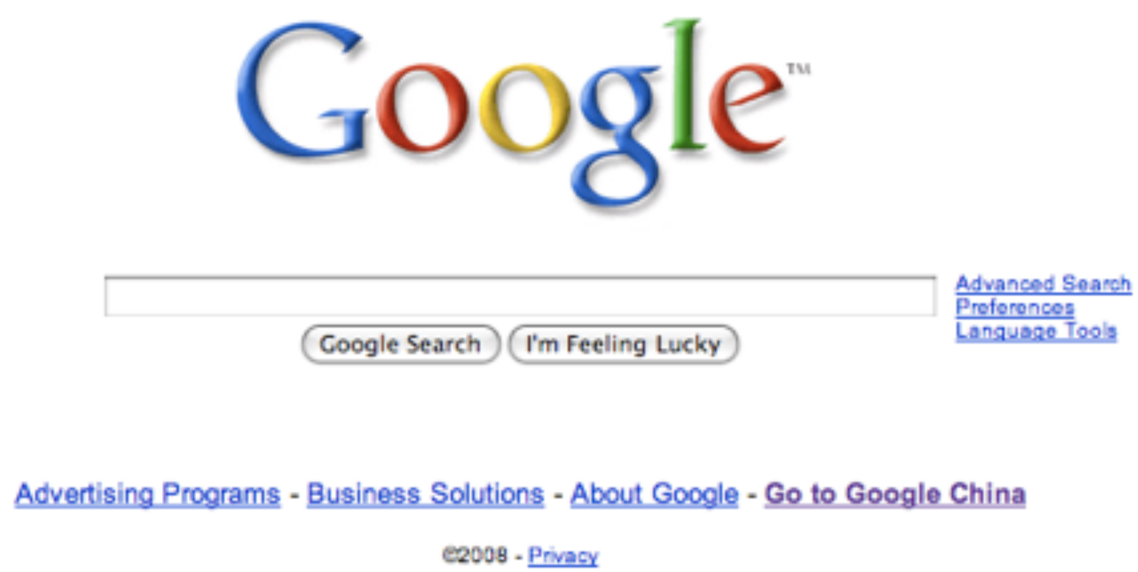
2015-11-05

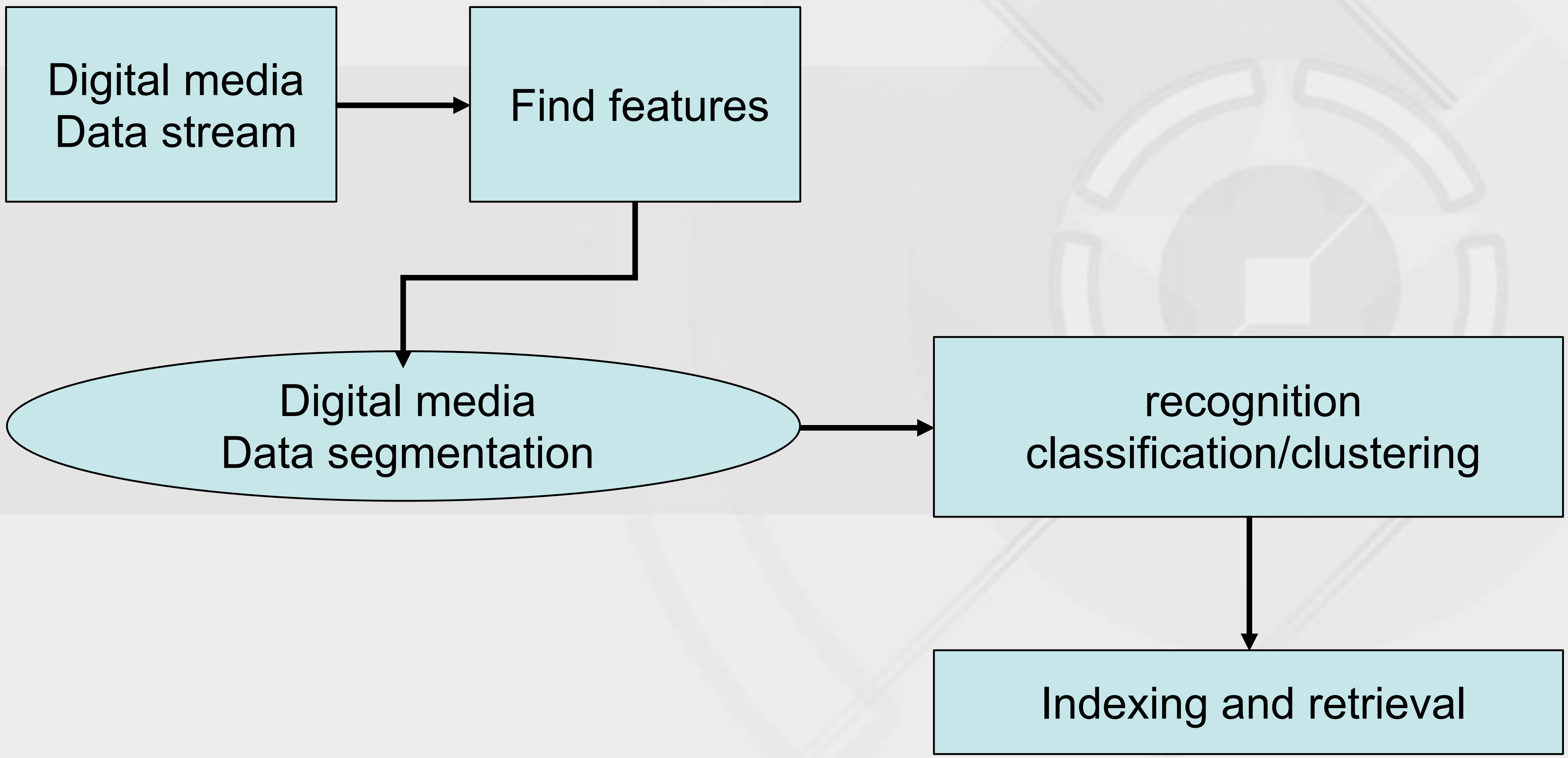
Main methods of digital media retrieval

- **Text-based** digital media retrieval

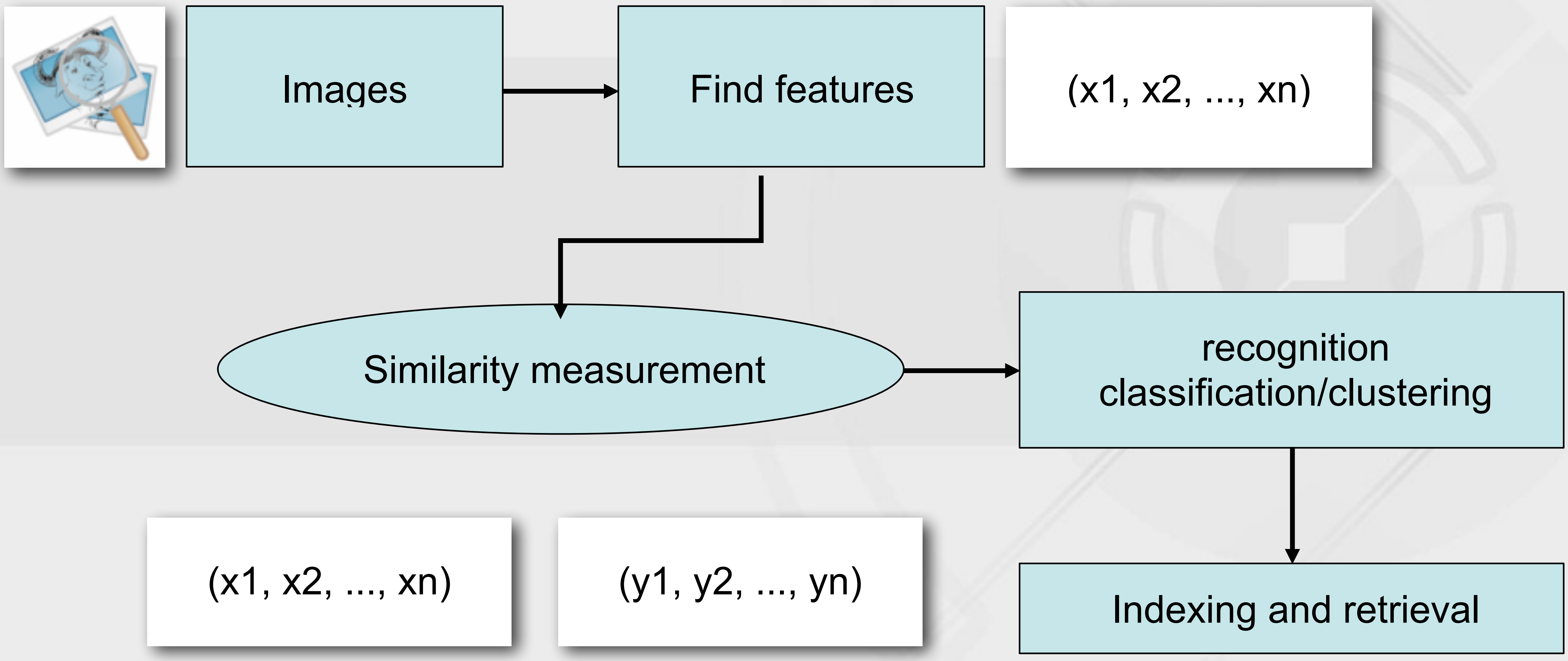


- **Content-based** digital media retrieval

The workflow of digital media analysis and retrieval



Workflow of CBIR



Features of image

- Finding out features of image is a key step of image retrieval
  - Image-based retrieval usually need to pre-construct feature database of images for retrieval

- Major image features:
  - Color features
  - Texture features
  - Shape features
  - Space relation features

Color features of image

- Color feature is a most widely used vision feature. It is mainly used to analyze color distributions in an image, including:
  - Color histogram
  - Color moments
  - Color set
  - Color clustering vectors
  - Color relation graph

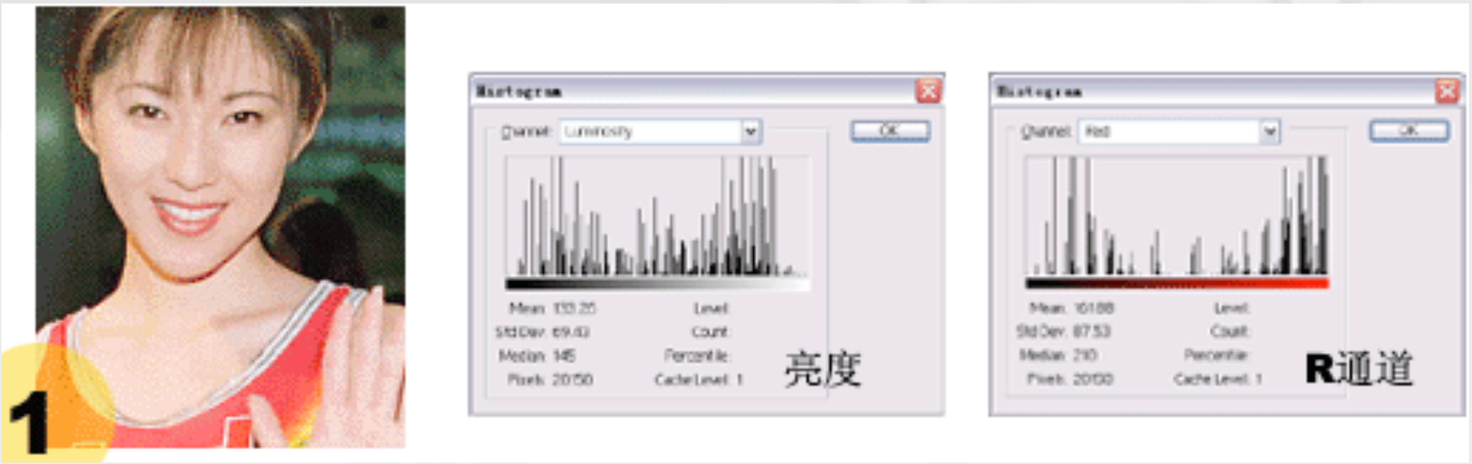


Image texture features

- Texture features are such vision features employed to measure homogeneous phenomenon in images. They are
  - independent to color or illuminance,
  - and are intrinsic features of object surfaces.

- Major texture features
  - Tamura texture features
  - Self-regression texture model
  - Transform based texture features
    - DWT，DFT，Garbor filter bank
  - others

Image shape features

- Shape features are computed out based on object segments or regions, mainly including
  - contour features
  - and regions features.

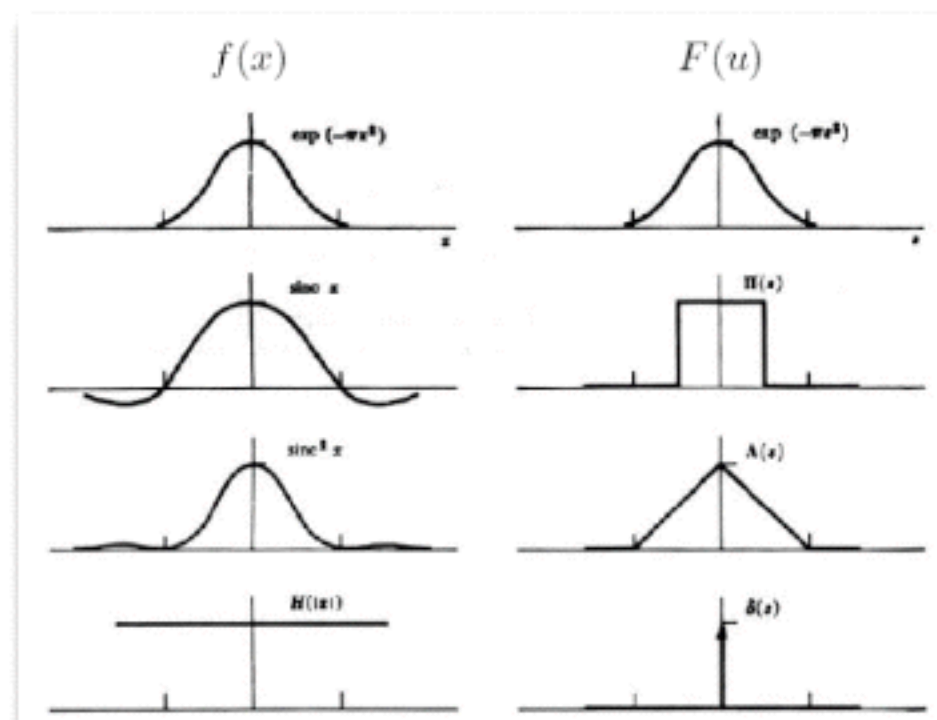
- Typical approaches include
  - Fourier shape description
  - Moment invariants

The Fourier Transform

- Represent function on a new basis
  - Think of functions as vectors, with many components
  - We now apply a linear transformation to transform the basis
    - dot product with each basis element

$$F(g(x,y))(u,v) = \iint_{\mathrm{R}^2} g(x,y) e^{-i2\pi(ux+vy)} dxdy$$

- In the expression, u and v select the basis element, so a function of x and y becomes a function of u and v
- basis elements have the form $e^{-i2\pi(ux+vy)}$



Discrete Fourier Transform

- 2D DFT

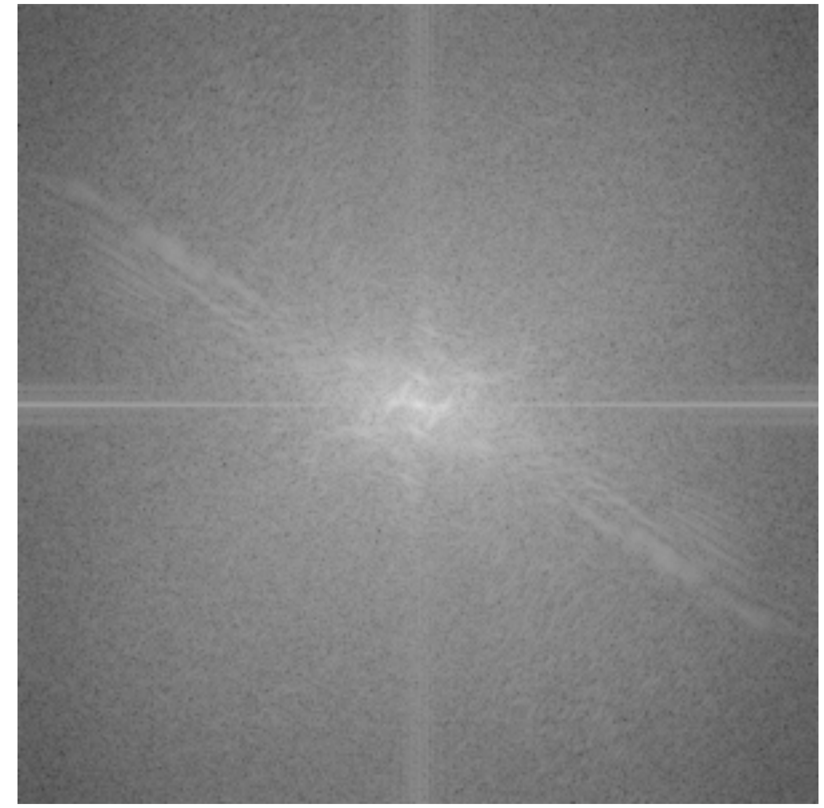
$$F(k,l) = \frac{1}{N^2} \sum_{a=0}^{N-1} \sum_{b=0}^{N-1} f(a,b)\, e^{-\iota 2\pi \left(\frac{ka}{N} + \frac{lb}{N}\right)}$$

- 2D IDFT

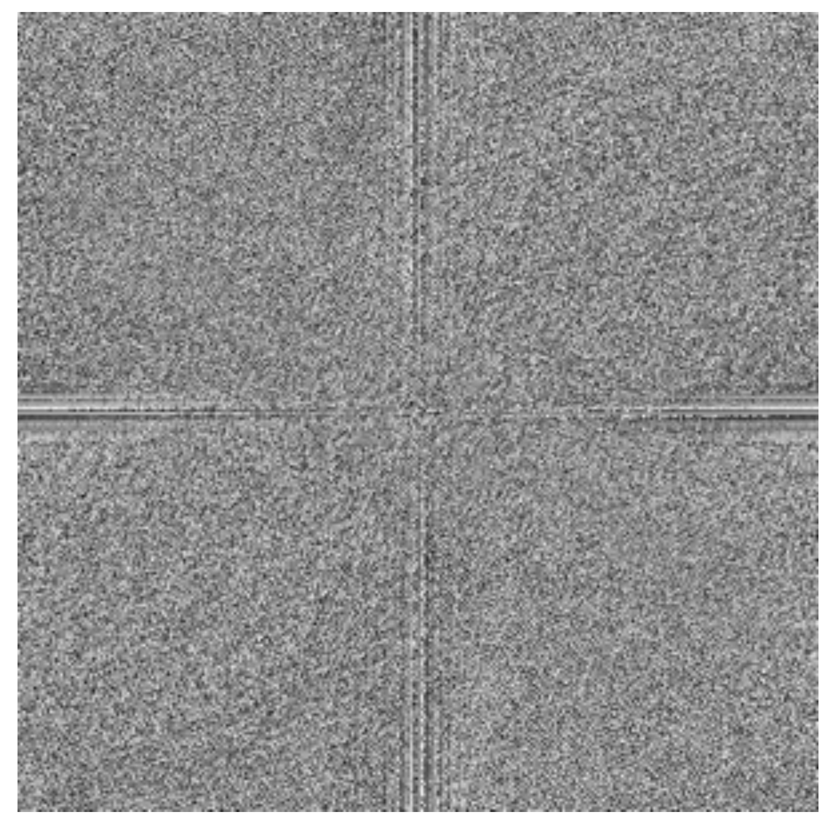
$$f(a,b) = \frac{1}{N^2} \sum_{k=0}^{N-1} \sum_{l=0}^{N-1} F(k,l)\, e^{\iota 2\pi \left(\frac{ka}{N} + \frac{lb}{N}\right)}$$

Zebra

Fourier
Transform



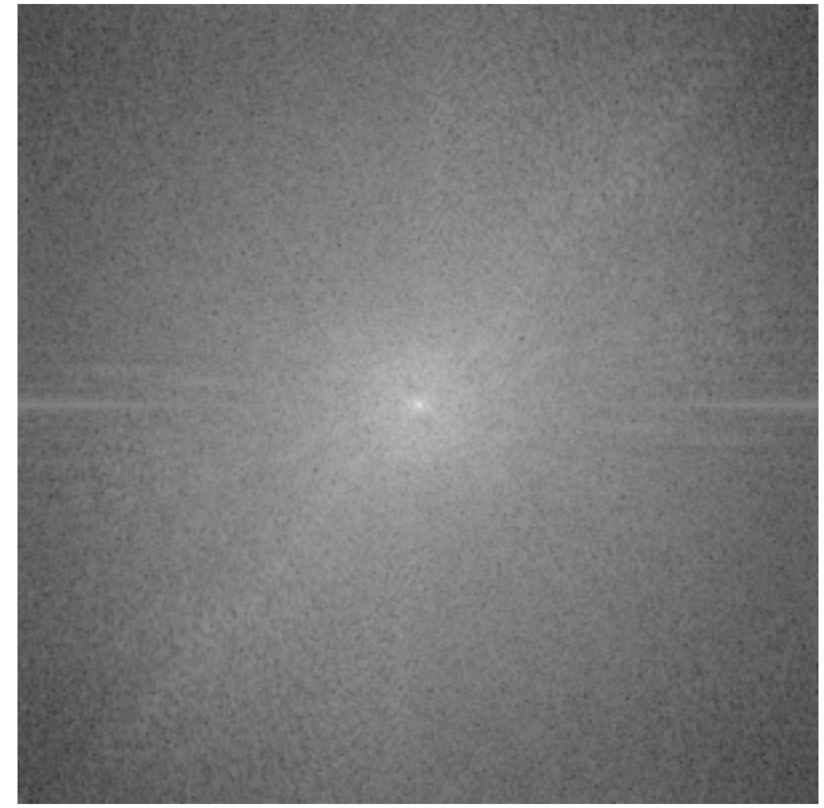
magnitude transform



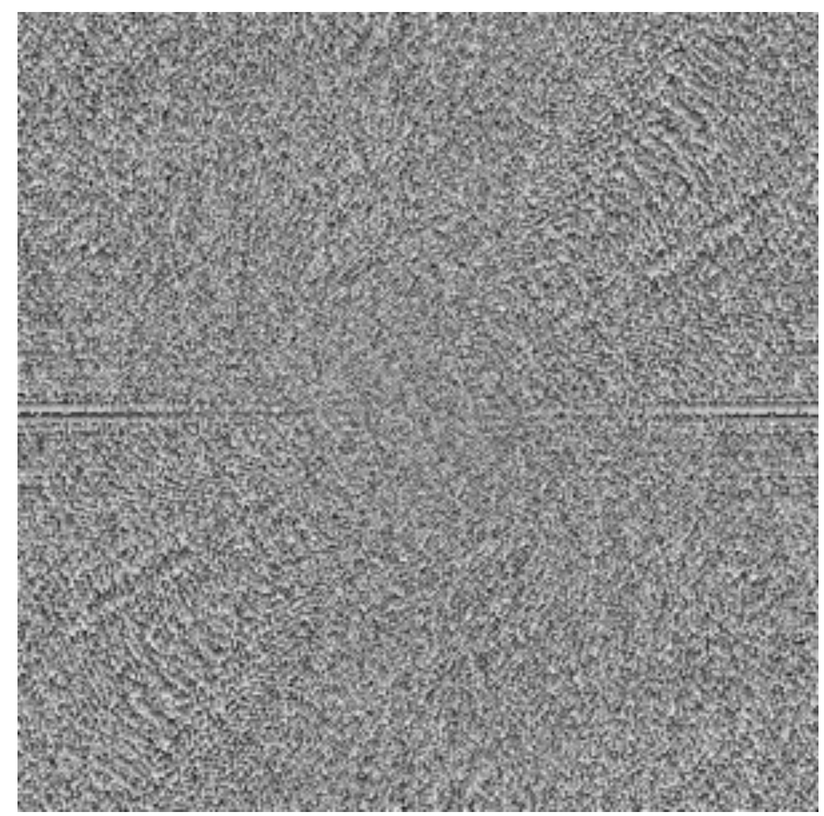
phase transform

Leopard

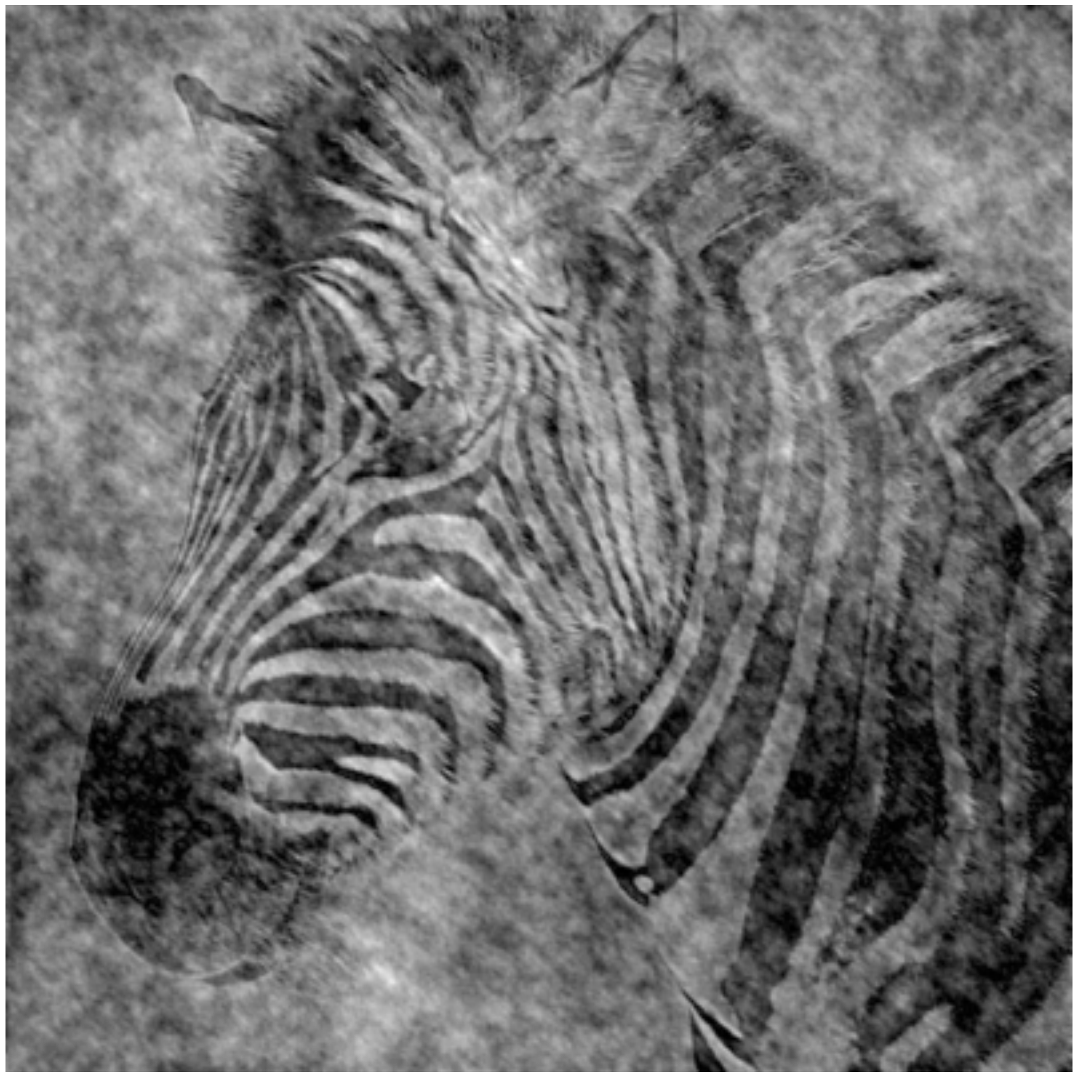
Fourier
Transform



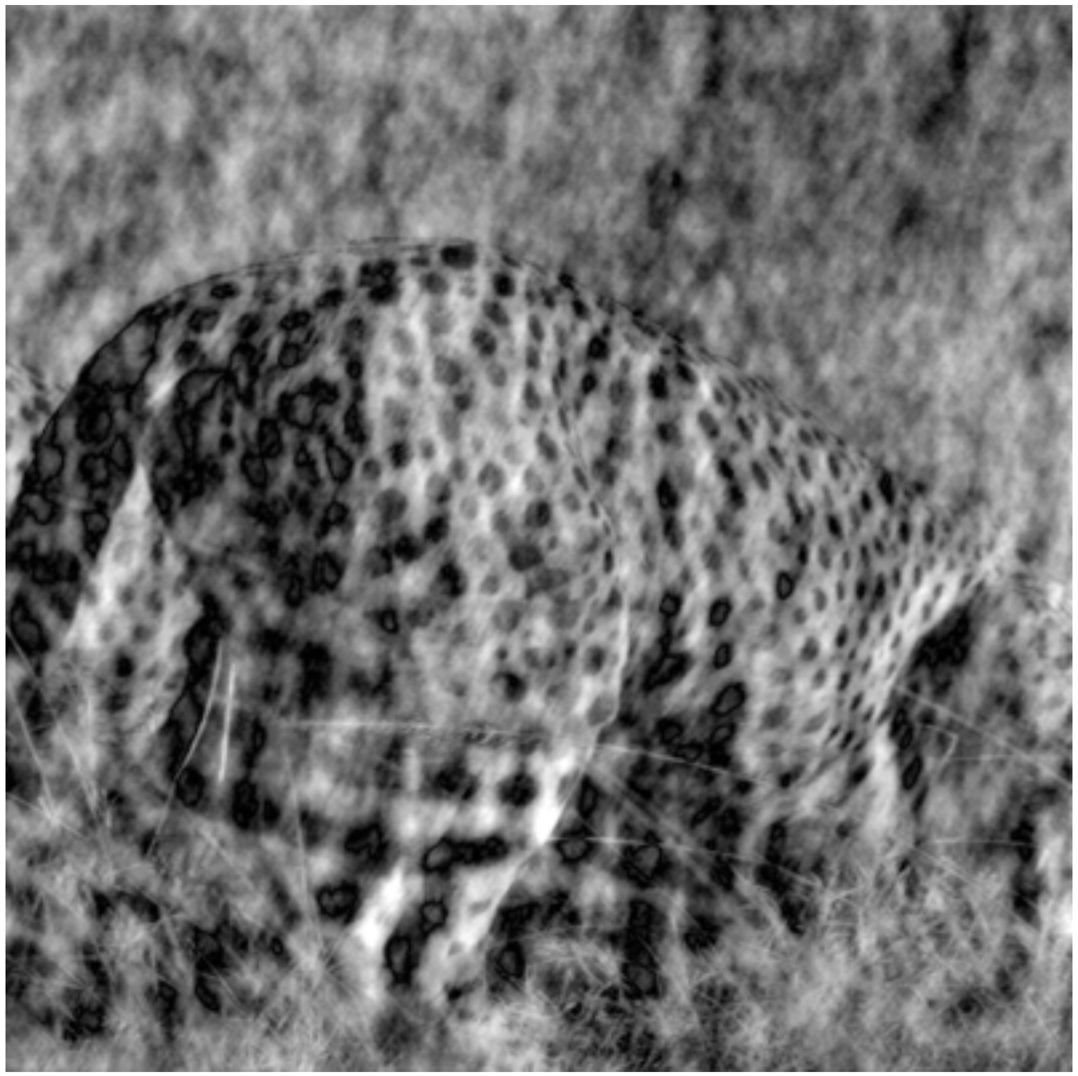
magnitude transform



phase transform



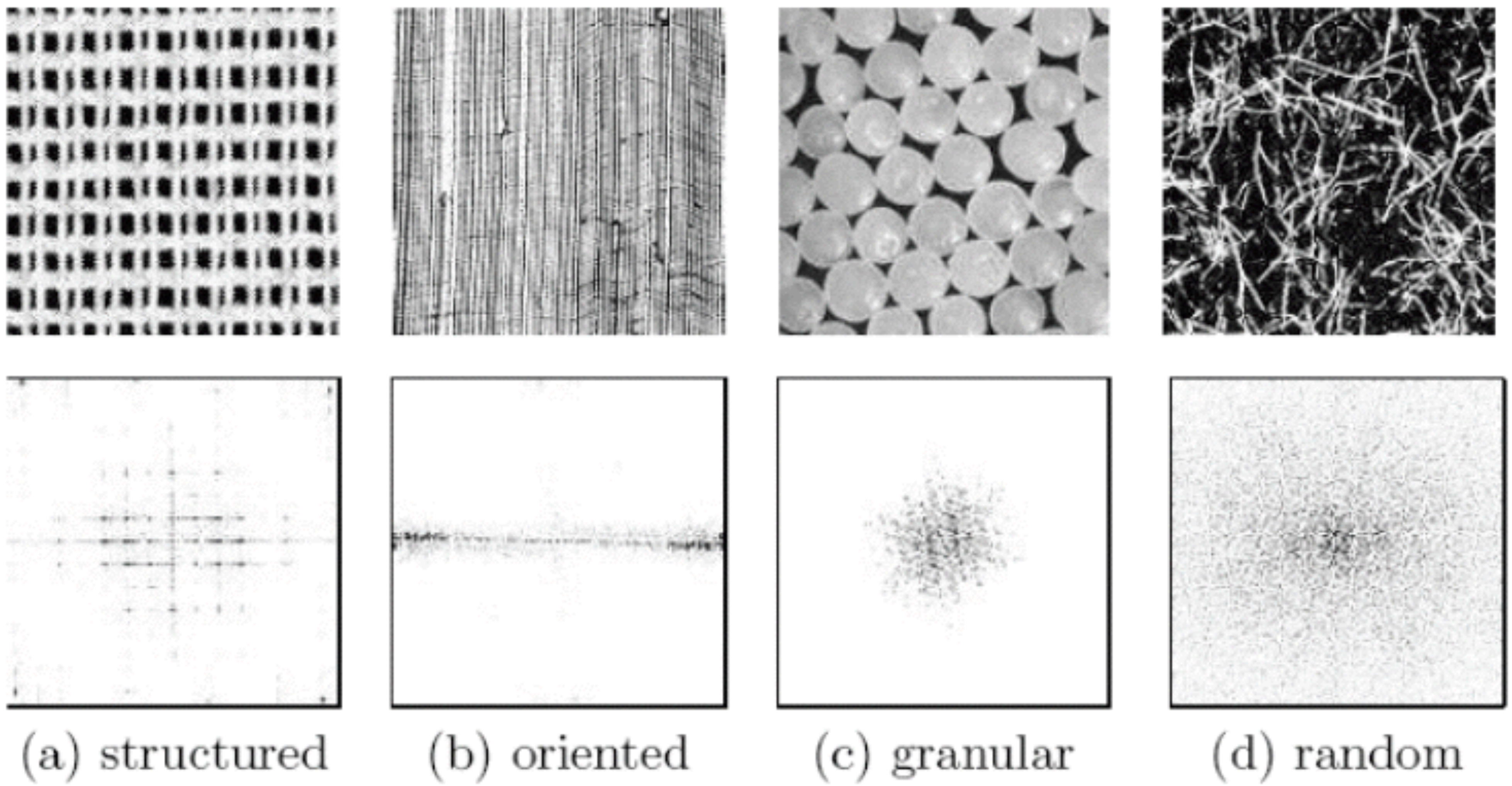
Zebra's phase
+ Leo's mag



Leo's phase
+ Zebra's mag

Natural Images and Their FT

phase
transform



- What happened to the FT patterns when the texture scale and orientation are changed?

Frequency Domain Features

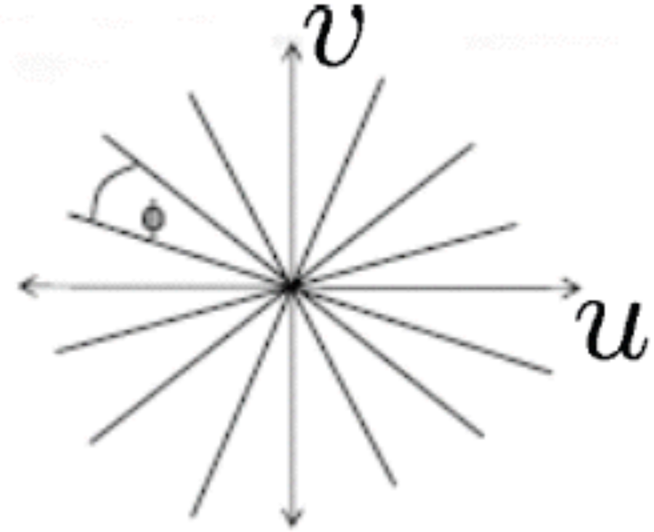
Fourier domain energy distribution

- Angular features (directionality)

$$V^{(a)}_{\theta_1\theta_2} = \int\int |F(u,v)|^2 du dv$$

where,

$$\theta_1 \leq \tan^{-1}[\frac{v}{u}] \leq \theta_2$$

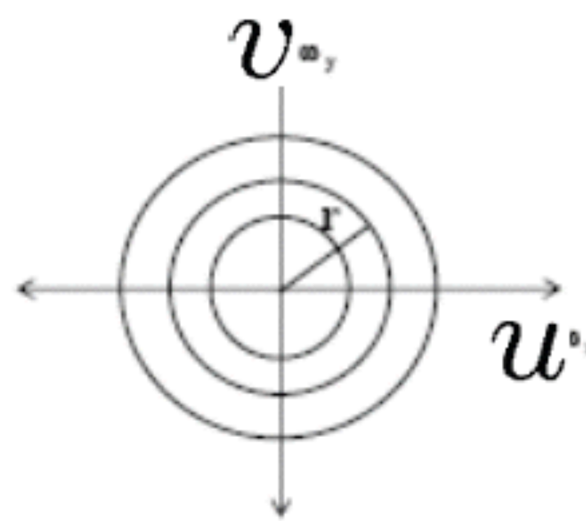


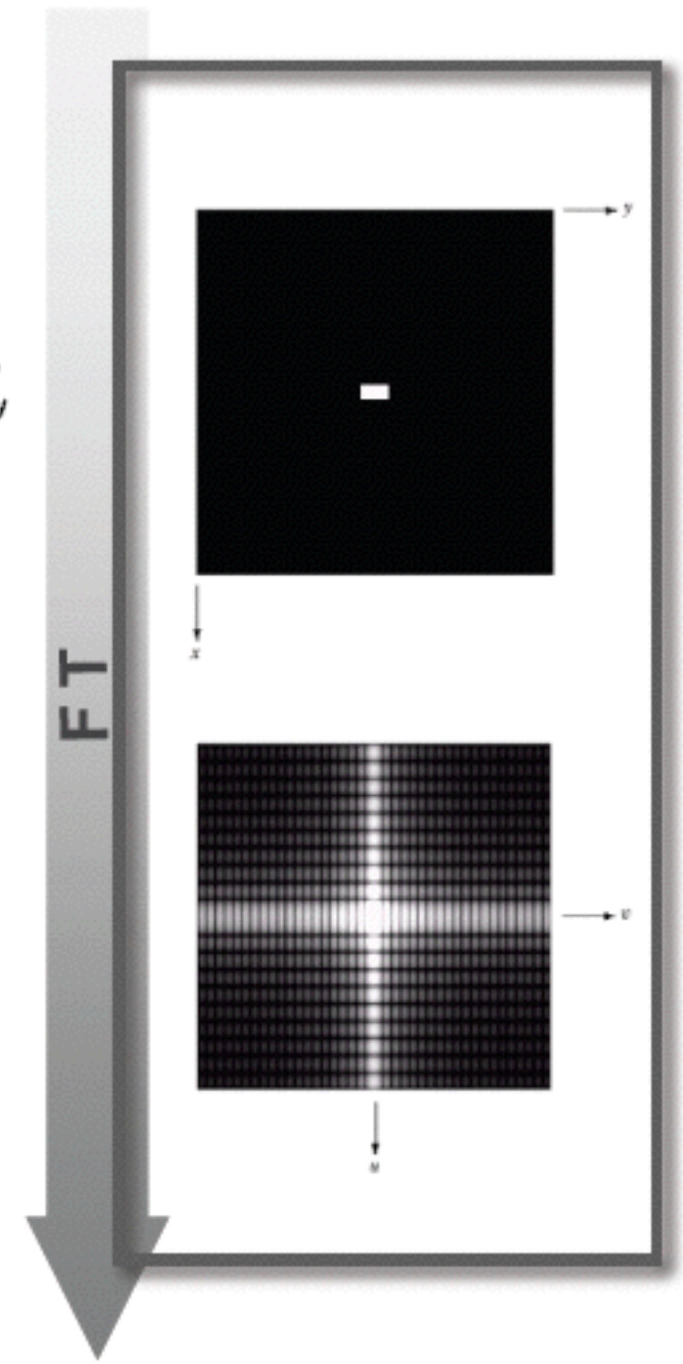
- Radial features (coarseness)

$$V^{(r)}_{r_1 r_2} = \int\int |F(u,v)|^2 du dv$$

where,

$$r_1 \leq u^2 + v^2 < r_2$$

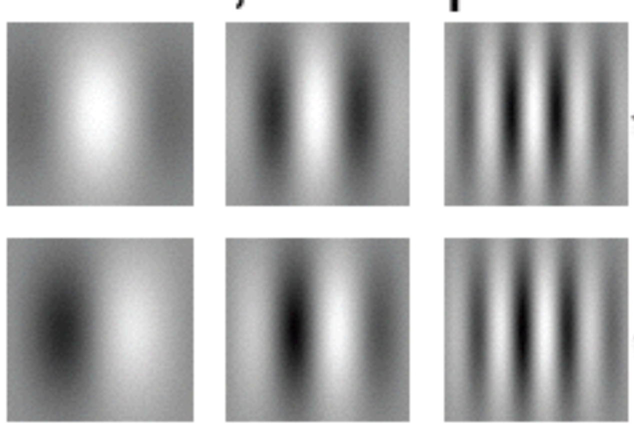




Uniform division may not be the best!!

Gabor Texture

- Fourier coefficients depend on the entire image (Global) → we lose spatial information
- Objective: local spatial frequency analysis
- Gabor kernels: looks like Fourier basis multiplied by a Gaussian
  - The product of a symmetric (even) Gaussian with an oriented sinusoid
  - Gabor filters come in pairs: symmetric and anti-symmetric (odd)
  - Each pair recover symmetric and anti-symmetric components in a particular direction
  - (k_x, k_y): the spatial frequency to which the filter responds strongly
  - σ : the scale of the filter. When σ = infinity, similar to FT
- We need to apply a number of Gabor filters are different scales, orientations, and spatial frequencies

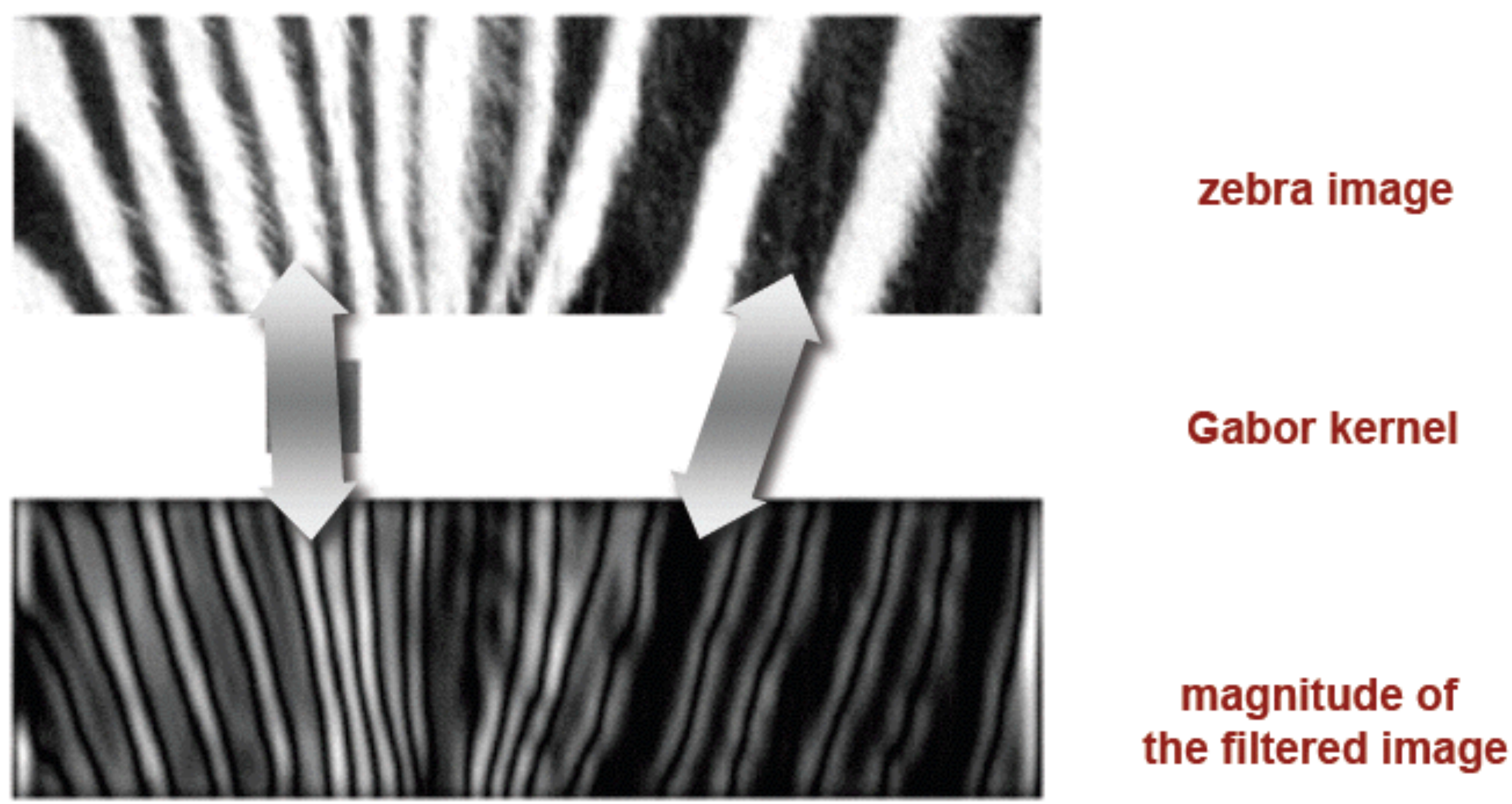


$$G_{symmetric}(x,y) = \cos(k_x x + k_y y) \exp -\frac{x^2+y^2}{2\sigma^2}$$

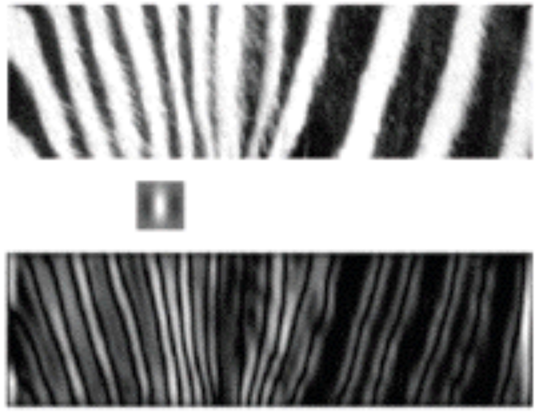
$$G_{anti-symmetric}(x,y) = \sin(k_x x + k_y y) \exp -\frac{x^2+y^2}{2\sigma^2}$$

Example – Gabor Kernel

- Zebra stripes at different scales and orientations and convolved with the Gabor kernel
- The response falls off when the stripes are larger or smaller
- The response is large when the spatial frequency of the bars roughly matches the windowed by the Gaussian in the Gabor kernel
- Local spatial frequency analysis



Gabor Texture (cont.)



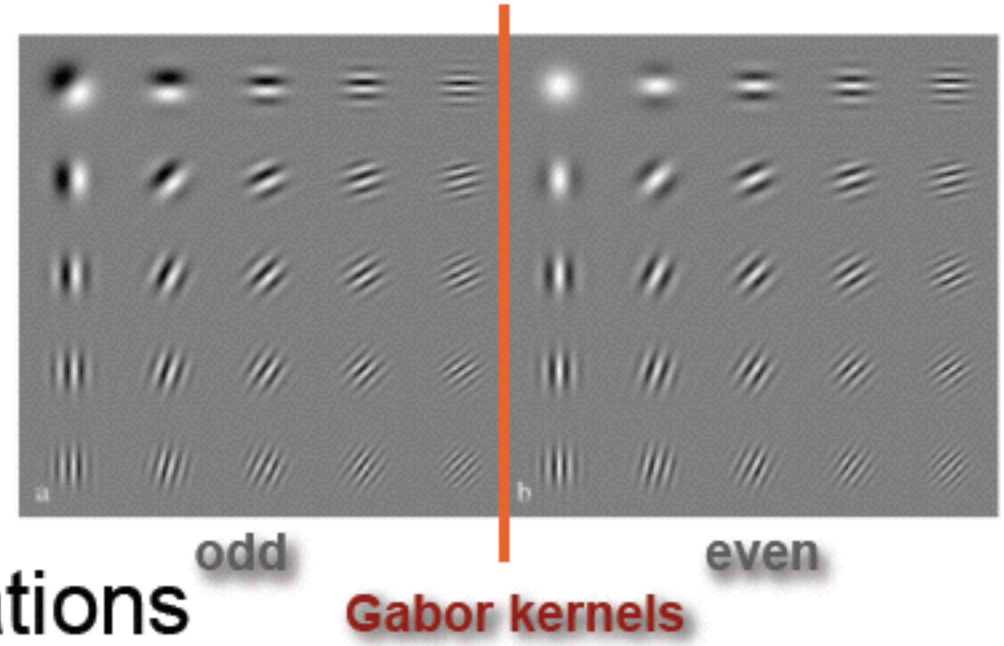
- Image $I(x,y)$ convoluted with Gabor filters h_{mn} (totally M x N)

$$W_{mn}(x,y) = \int I(x_1,y_1)h_{mn}(x-x_1, y-y_1)dx_1dy_1$$

- Using first and 2nd moments for each scale and orientations

$$\mu_{mn} = \int\int |W_{mn}(x,y)|dxdy$$

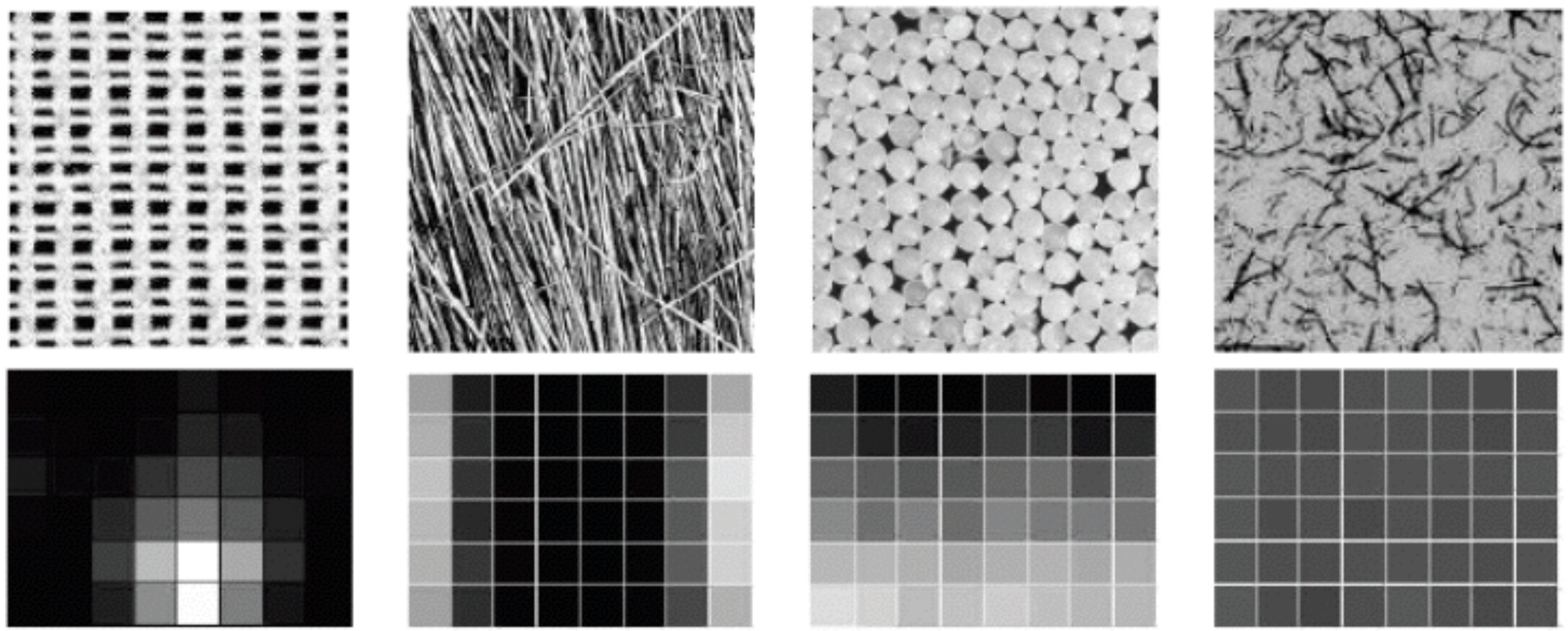
$$\sigma_{mn} = \sqrt{\int\int (|W_{mn}(x,y)| - \mu_{mn})^2 dxdy}$$



- Features: e.g., 4 scales, 6 orientations → 48 dimensions

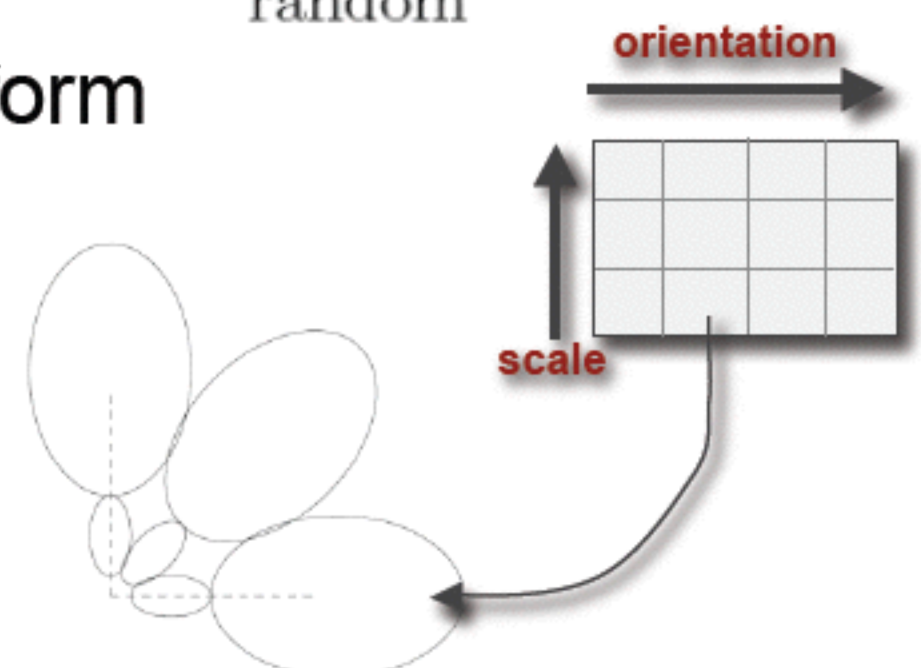
$$\bar{v} = [\mu_{00}, \sigma_{00}, \mu_{01}, \ldots, \mu_{35}, \sigma_{35}]$$

Gabor Texture (cont.)



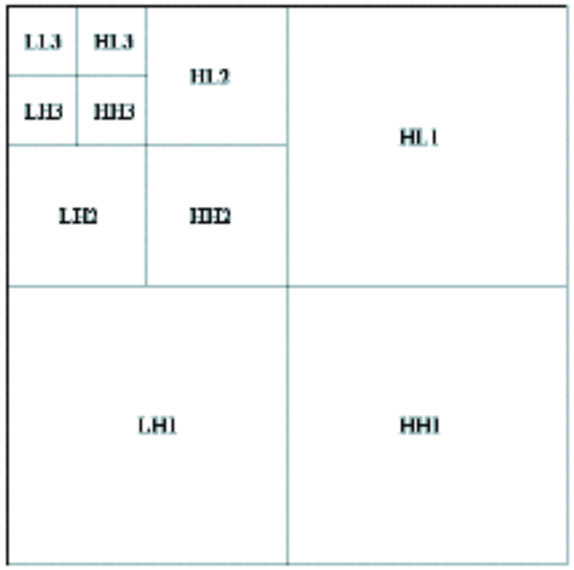
structured oriented granular random

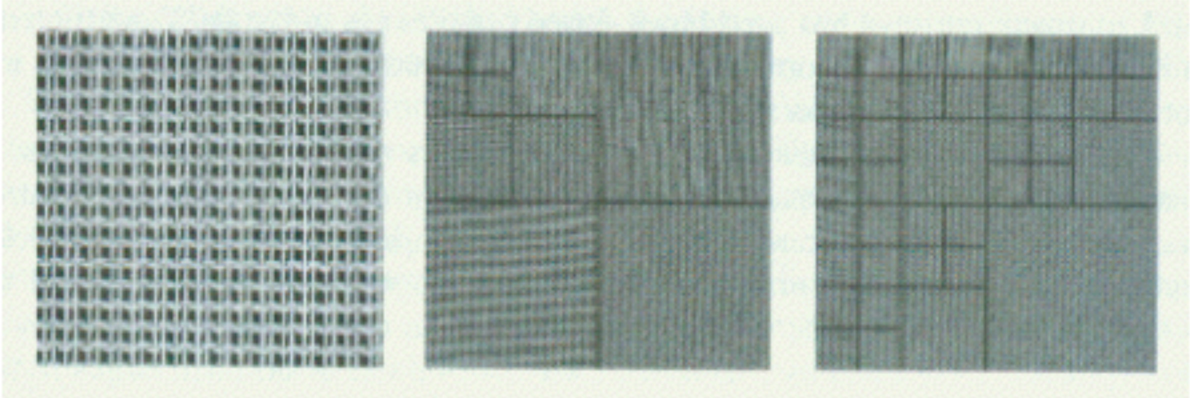
- Arranging the mean energy in a 2D form
  - structured: localized pattern
  - oriented (or directional): column pattern
  - granular: row pattern
  - random: random pattern



Wavelet Features (PWT, TWT)

- Wavelet
  - Decomposition of signal with a family of basis functions with recursive filtering and sub-sampling
  - Each level, decomposes 2D signal into 4 subbands, LL, LH, HL, HH (L=low, H=high)
- PWT: pyramid-structured wavelet transform
  - Recursively decomposes the LL band
  - Feature dimension (3x3x1+1)x2 = 20
- TWT: pyramid-structured wavelet transform
  - Some information in the middle frequency channels
  - Feature dimension 40x2 = 80





original image PWT TWT

Texture Comparisons

[Ma'98]

- Retrieval performance of different texture features according to the number of relevant images retrieved at various scopes using Corel Photo galleries

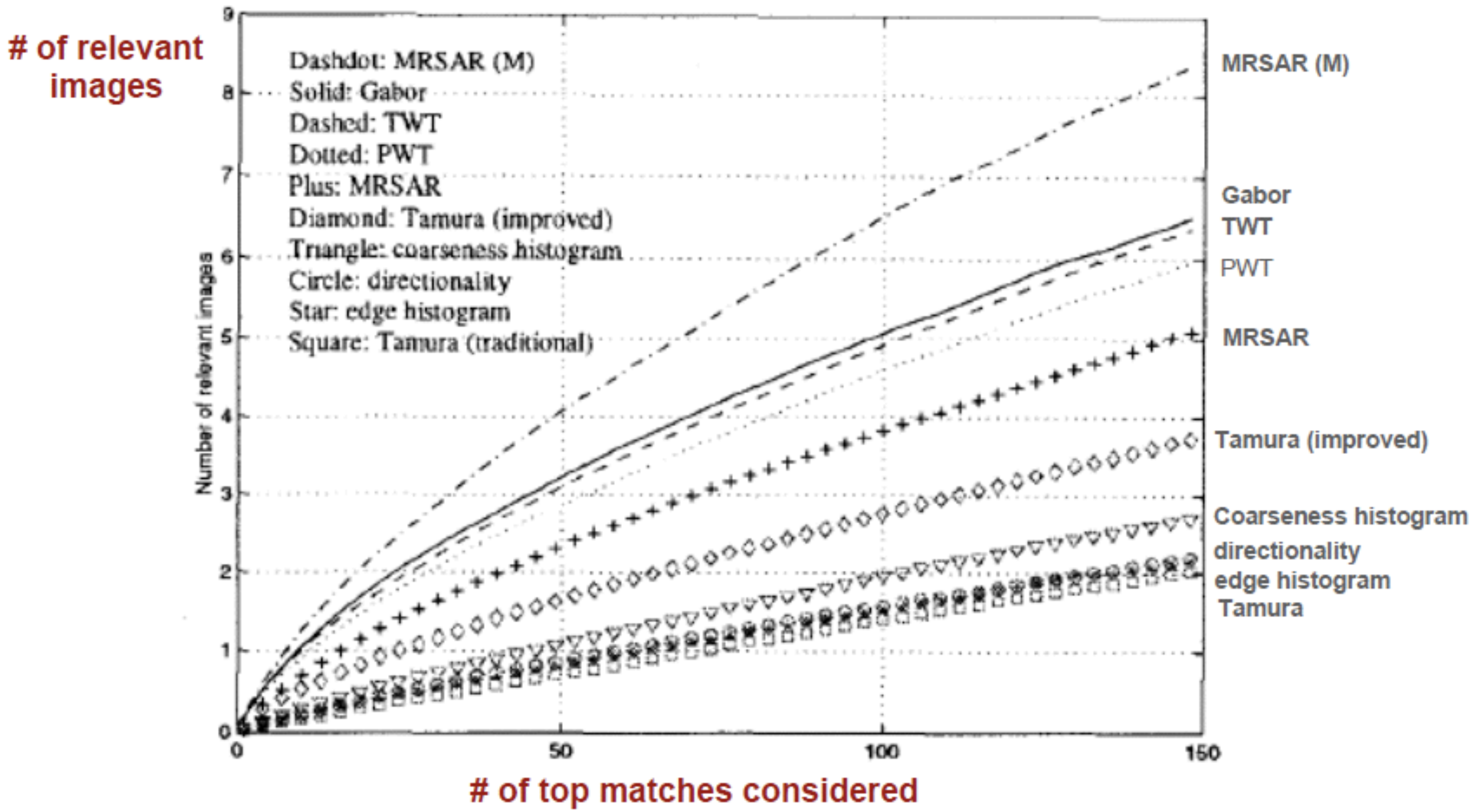
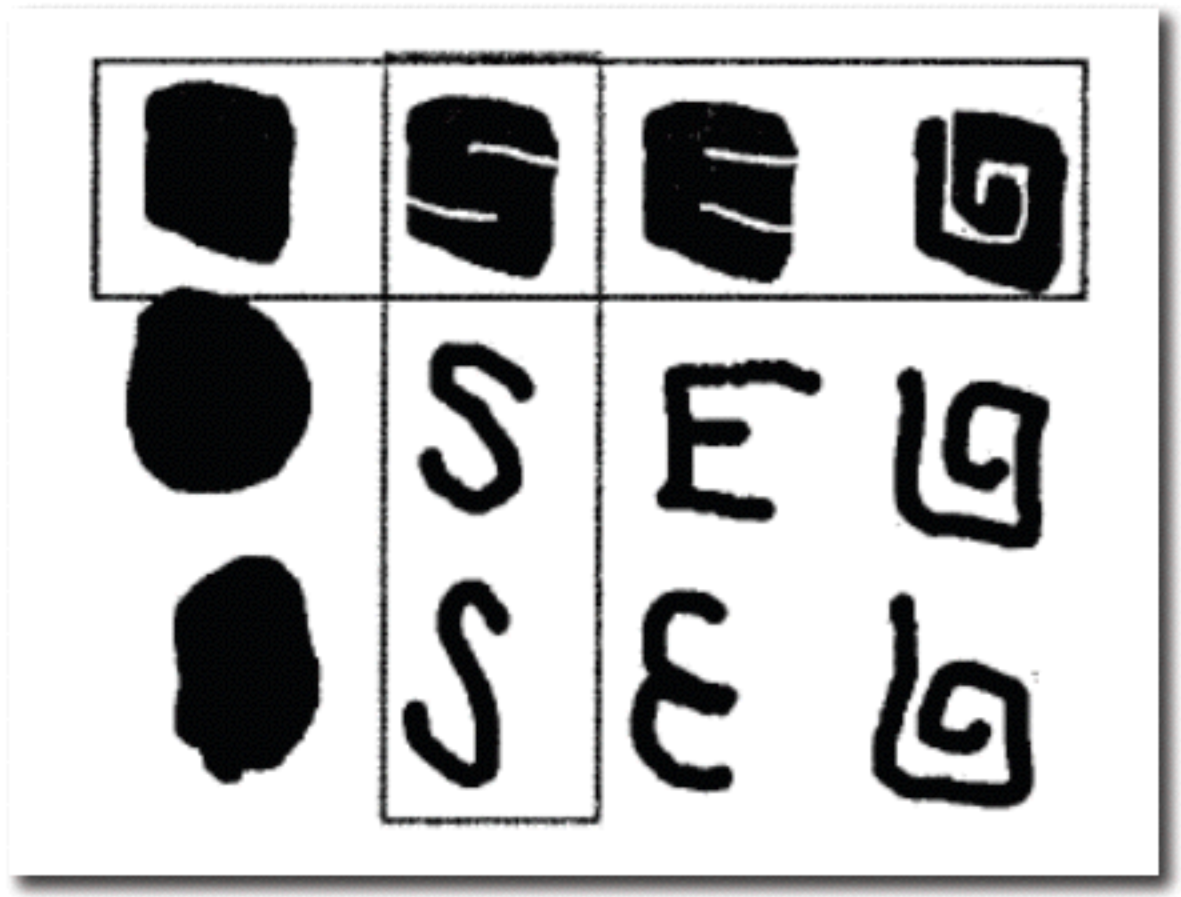


Image shape features

- Shape features are computed out based on object segments or regions, mainly including
  - contour features
  - and regions features.

- Typical approaches include
  - Fourier shape description
  - Moment invariants

Region-based vs. Contour-based Descriptor



- Columns indicate contour similarity
  - Outline of contours
- Rows indicate region similarity
  - Distribution of pixels

Region-based Descriptor

- Express pixel distribution within a 2D object region
- Employs a complex 2D Angular Radial Transformation (ART)
  - 35 fields each of 4 bits
- Rotational and scale invariance
- Robust to some non-rigid transformation
- L_1 metric on transformed coefficients
- Advantages
  - Describing complex shapes with disconnected regions
  - Robust to segmentation noise
  - Small size
  - Fast extraction and matching

Contour-based Descriptor

- It's based on Curvature (曲率) Scale-Space (CSS) representation
- Found to be superior to
  - Zernike moments
  - ART
  - Fourier-based
  - Turning angles
  - Wavelets
- Rotational and scale invariance
- Robust to some non-rigid transformations
- For example
  - Applicable to (a)
  - Discriminating differences in (b)
  - Finding similarities in (c)-(e)

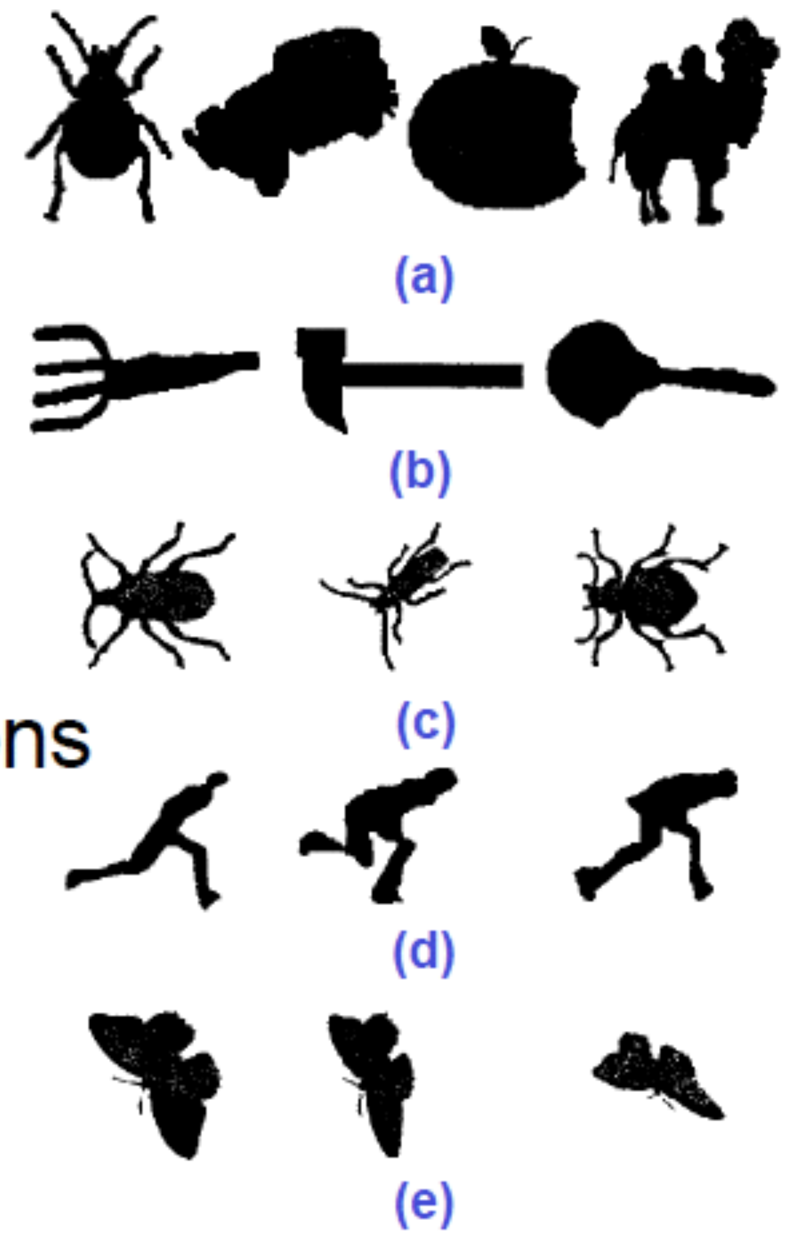
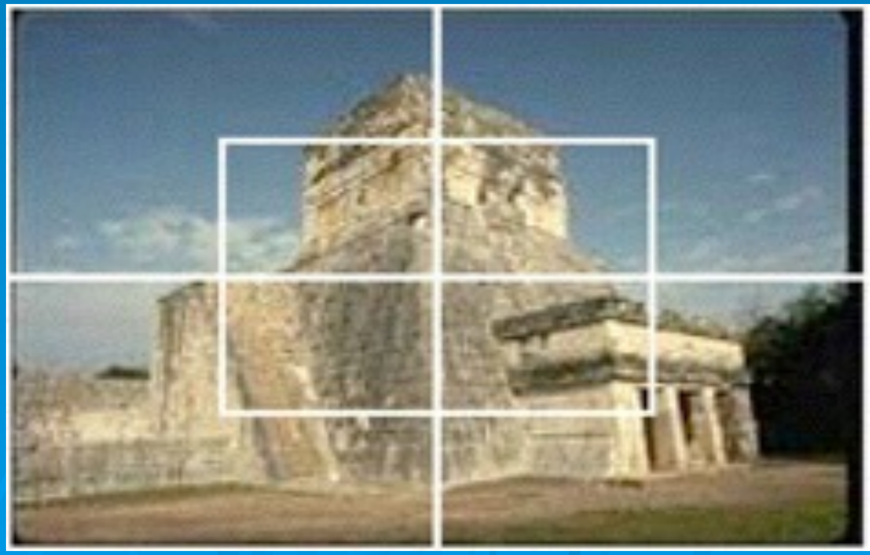


Image Retrieval Phase (cont.)

- Query by color anglogram (cont.)
  - Convert RGB to HSV [wikipedia]

  - Global and sub-image histogram forms LSI matrix.



[Zhao & Grosky 2002]

$$\longrightarrow \quad (x_1, x_2, \ldots, x_n)$$

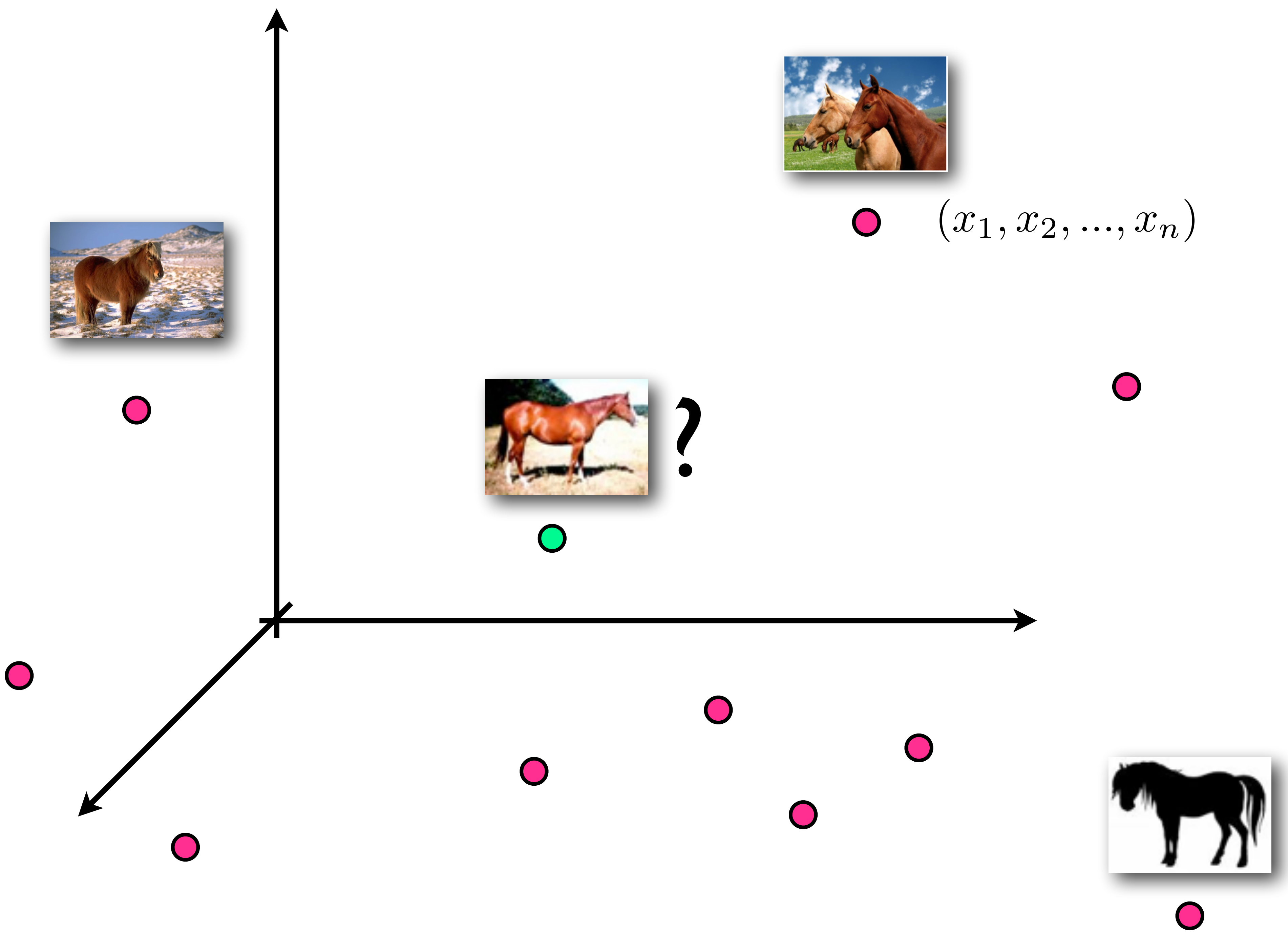
Image A

Feature extraction

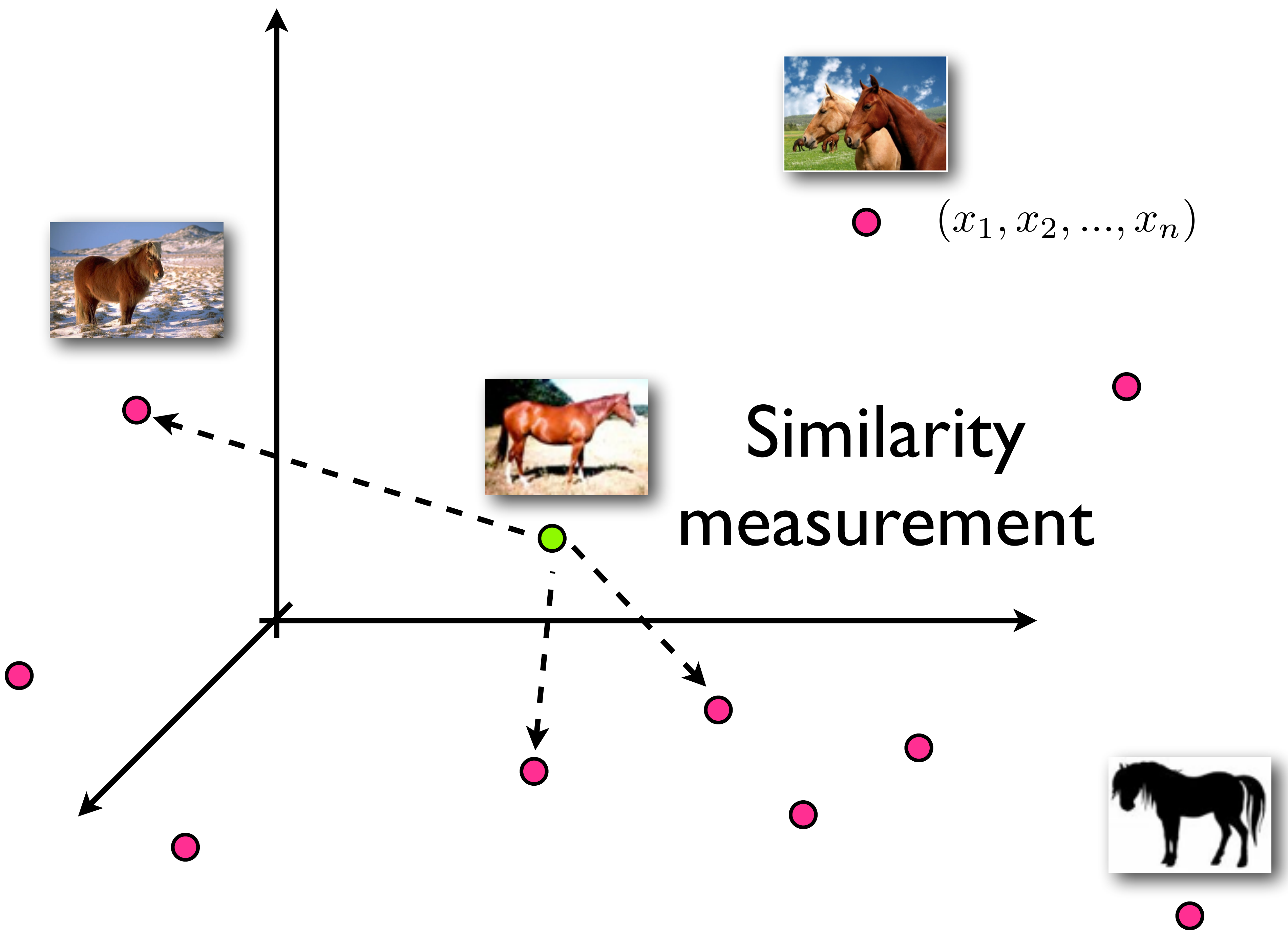
$$\longrightarrow \quad (y_1, y_2, \ldots, y_n)$$

Image B

A geometrical view of CBIR



A geometrical view of CBIR



A geometrical view of CBIR

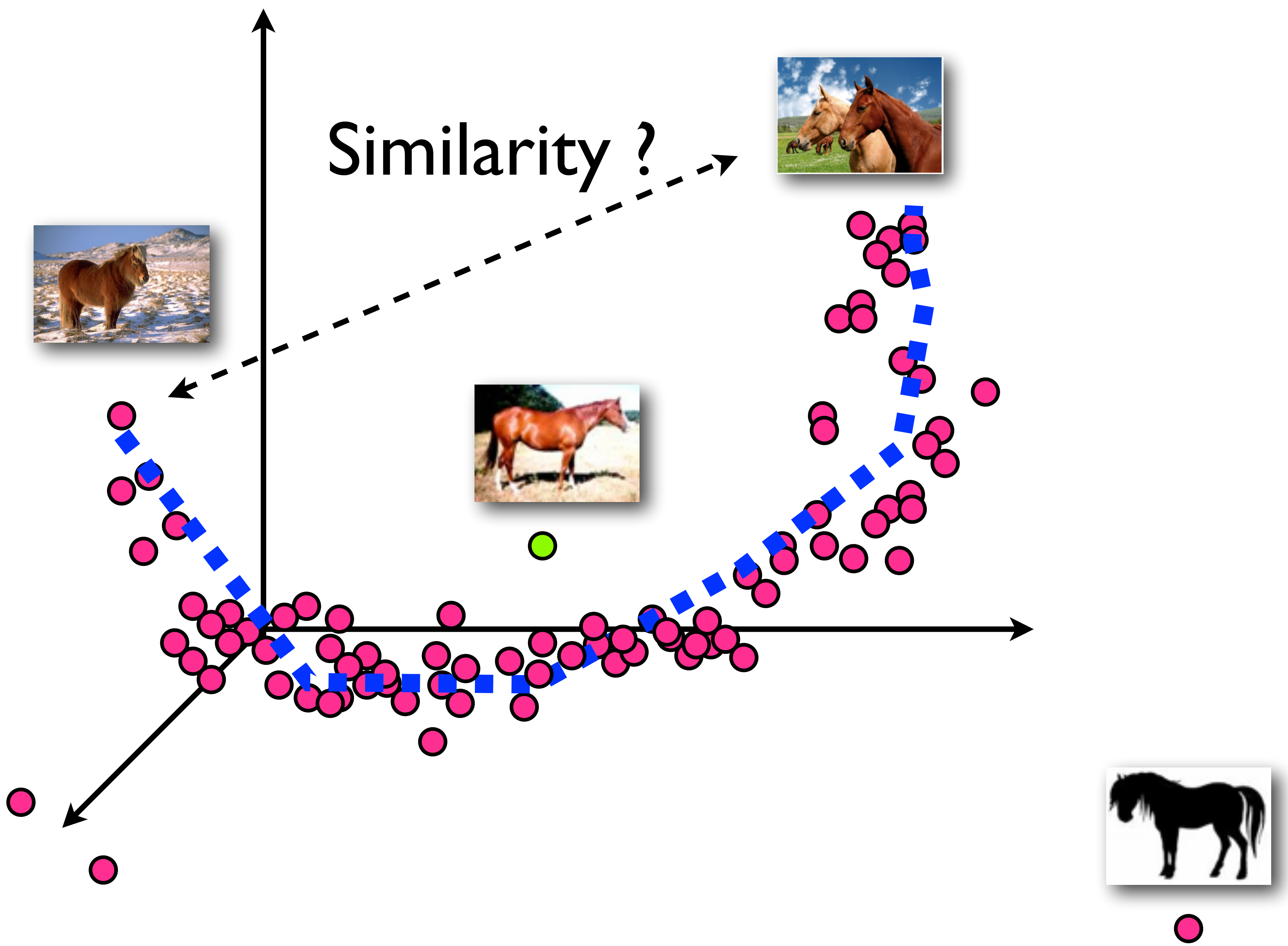


Image similarities

- How to measure similarity of different images base on features?
  - Image features always form into a fixed-length feature vector.
  - The similarity therefore can be measure by
    - Euclidian distance
    - Histogram intersection
    - Quadratic distance
    - Mahalanobis distance (马氏距离)
    - Non-geometrical similarity

Practical image retrieval systems

- QBIC (Query By Image Content)
    - http://www.qbic.almaden.ibm.com/
- Virage
    - http://wwwvirage.com/cgi-bin/query-e
- RetrievalWare
    - http://vrw.excalib.com/cgi-bin/sdk/cst/cst2.bat
- Photobook

- MARS
    - http://jadzia.ifp.uiuc.edu:8000

Practical image retrieval systems (cont.)

- Most existing image retrieval systems have one or more of following functions features:
  - –Random browsing
  - –Classified browsing

  - –Example based retrieval
  - –Sketch based retrieval
  - –Texture based retrieval

2. music retrieval techniques

Content based music retrieval

- 說明
  - 用聲音的內容為根據，做音樂的檢索
- 目的
  - 讓使用者可以用自然的方式點選歌曲

http://www.soundhound.com/

Free Version of SoundHound
Now Available for iOS and Android

Highlights

Blazing fast music identification

Sing & Hum recognition

Voice-directed music search

In-app lyrics

Special on iPad:

Big, beautiful lyrics and music videos

The SoundHound Ticker

Version 3.3.1 for iPhone, iPod touch and iPad
Version 2.0.1 for Android

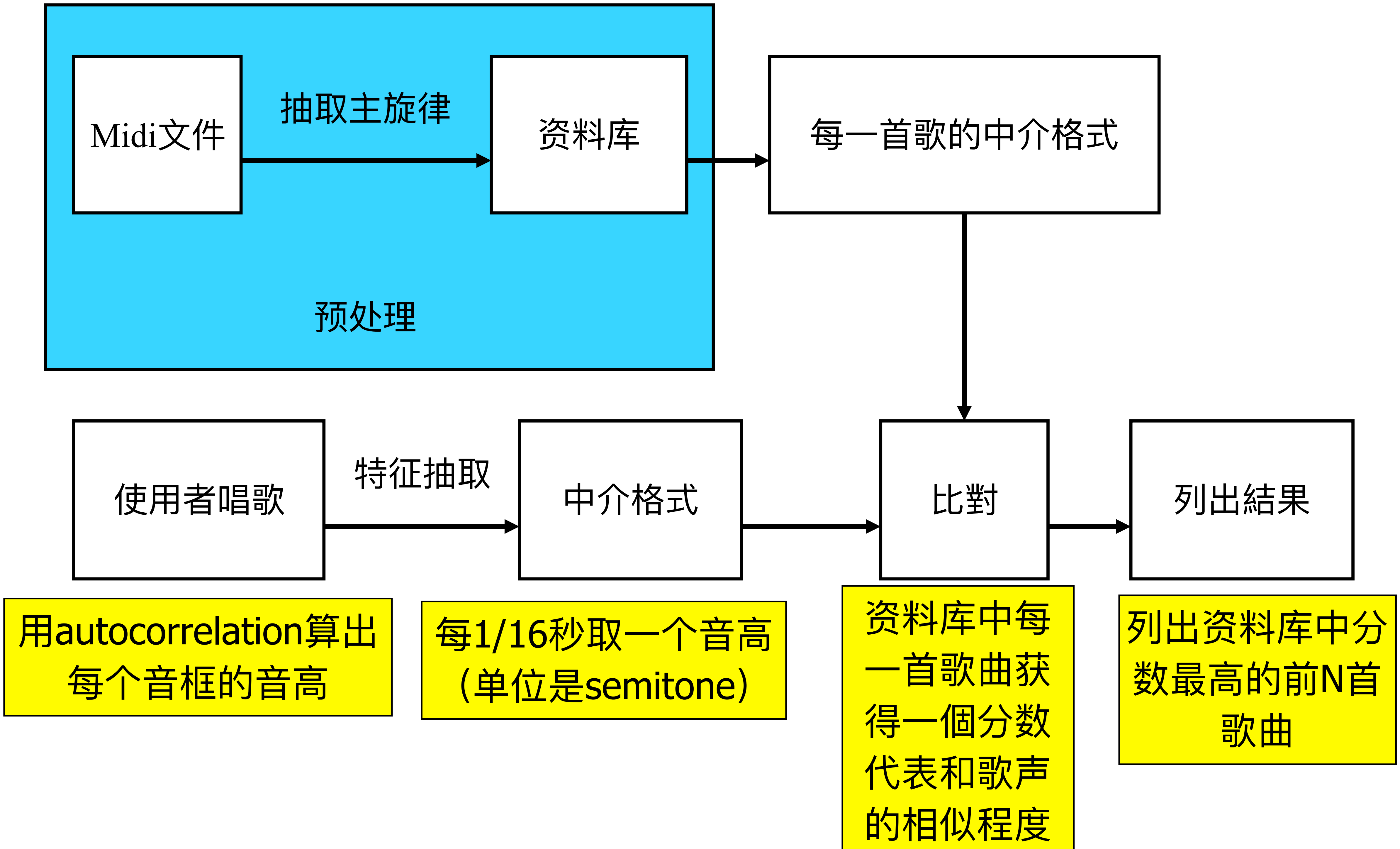
- SoundHound (free): 5 IDs per month App Store

- SoundHound ∞: unlimited App Store

Content based music retrieval

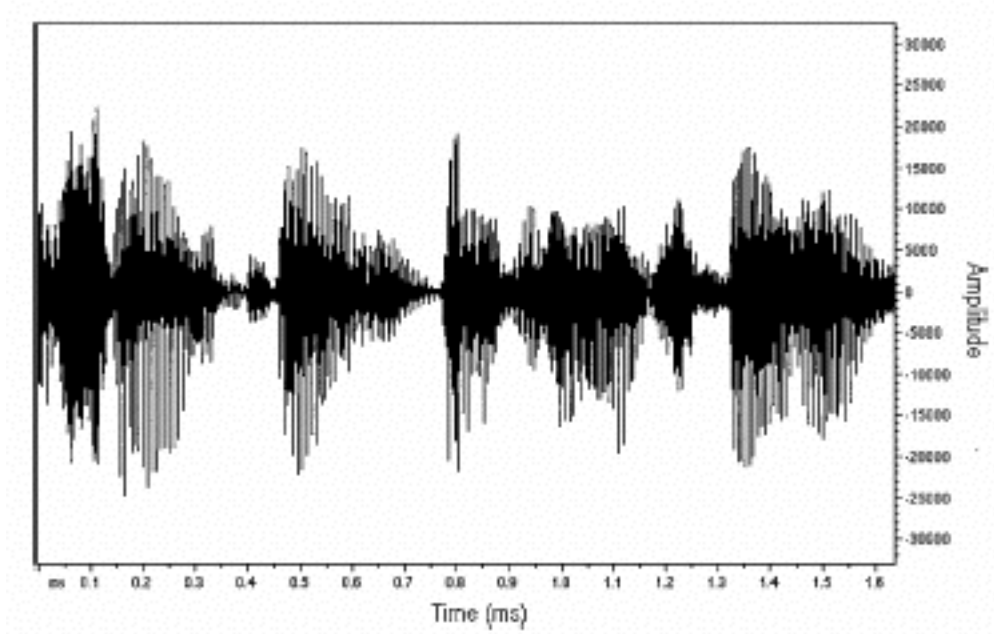
- 困難
  - 使用者的節奏（tempo）快慢不同、拍子不準、音調（key）高低不同
  - 若允許使用者從歌的任意處唱，計算量很大

CBMR系统流程图


Midi文件
抽取主旋律
资料库
每一首歌的中介格式
预处理
使用者唱歌
特征抽取
中介格式
比對
列出結果
用autocorrelation算出每个音框的音高
每1/16秒取一个音高(单位是semitone)
资料库中每一首歌曲获得一個分数代表和歌声的相似程度
列出资料库中分数最高的前N首歌曲

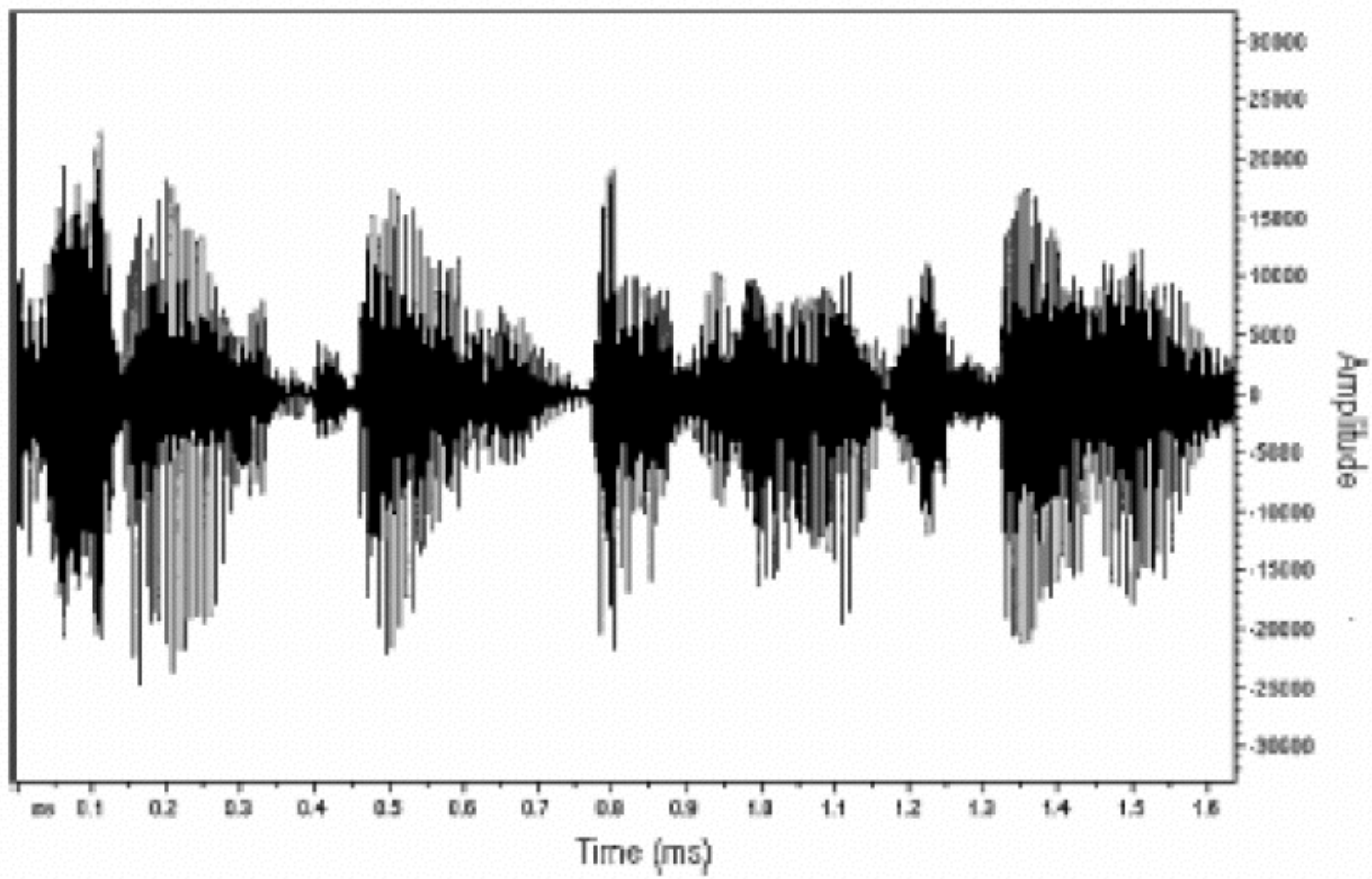
Main Audio Features

- Time-Domain Features
  - Average Energy
  - Zero Crossing Rate
  - Silence Ratio
- Frequency-Domain Features
  - Sound Spectrum
  - Bandwidth
  - Energy Distribution
  - Harmonicity
  - Pitch
- Spectrogram



Time-Domain Features

- Amplitude-time representation of an audio signal



Time-Domain Features (2)

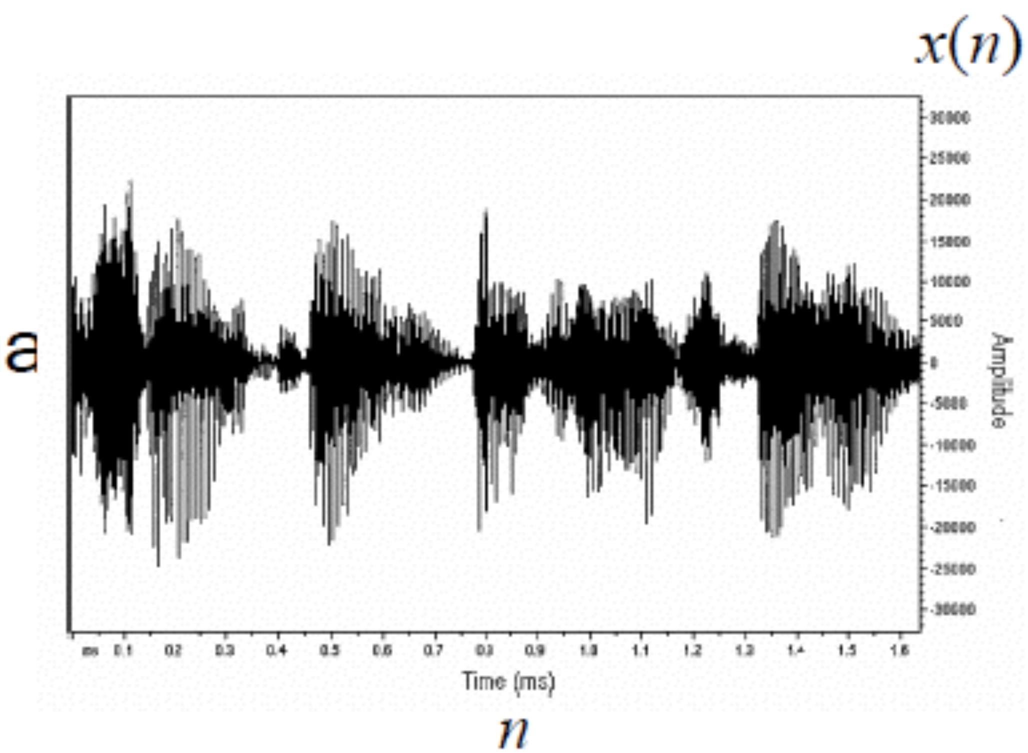
- Average Energy
  - Indicates the loudness of the audio signal

$$E = \frac{\sum_{n=1}^{N-1} x(n)^2}{N}$$

- Zero Crossing Rate
  - Indicates the frequency of signa amplitude sign change

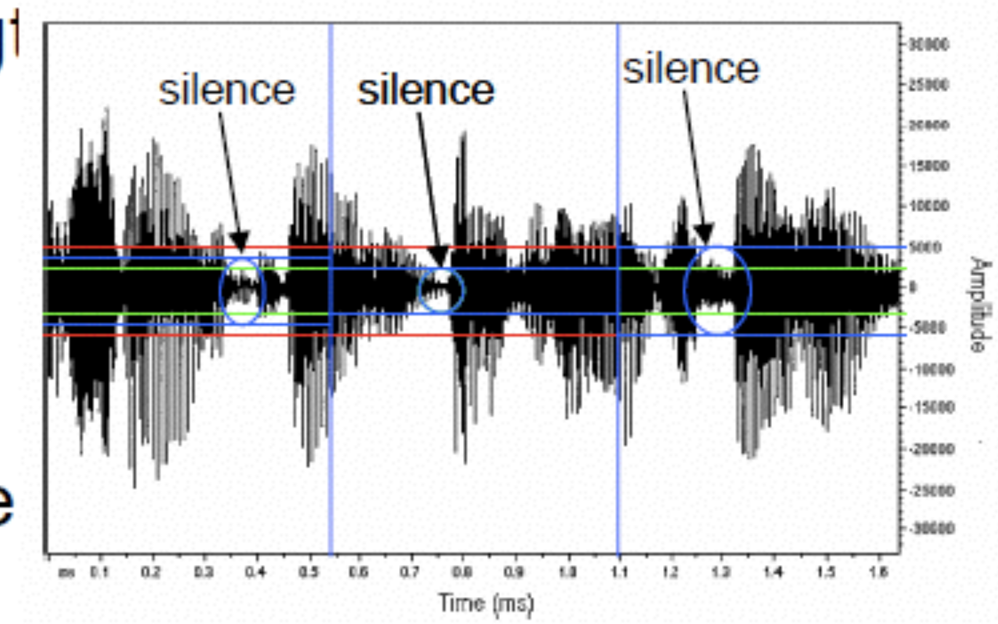
$$ZC = \frac{\sum_{n=1}^{N-1} \mathrm{sgn}[x(n)] - \mathrm{sgn}[x(n-1)]}{2N}$$

$$\mathrm{sgn}(a) = \begin{cases} 1 & a > 0 \\ 0 & a = 0 \\ -1 & a < 0 \end{cases}$$



Time-Domain Features (3)

- Silence Ratio
  - Indicates the proportion of the sound piece that is silent
  - Silence is a period within which the absolute amplitude values of a certain number of samples are below a certain threshold
  - Silence ratio is calculated as the ratio between the sum of silent periods and the total lengt

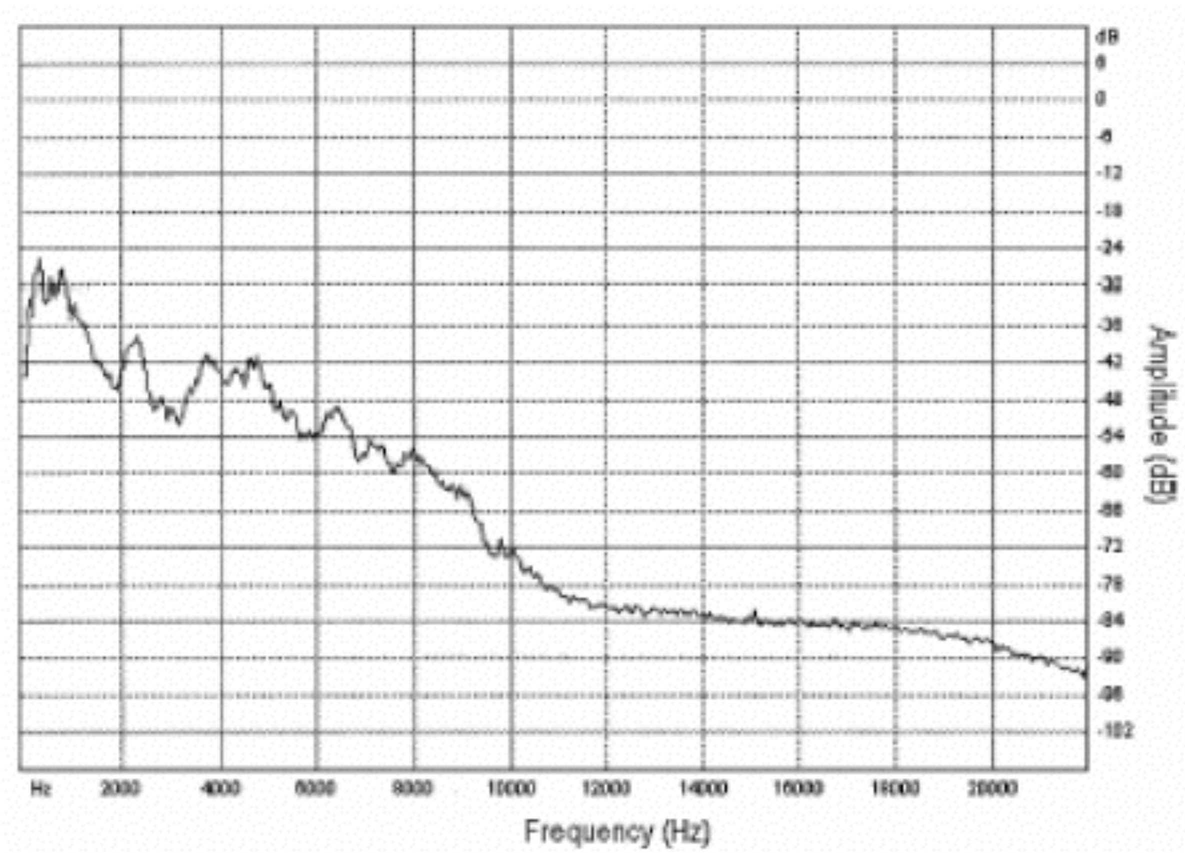


Approaches:

1. Fixed Threshold
2. Select Reference Silence Value
3. Adaptive Silence Thresholds

Frequency-Domain Features

- Sound Spectrum



Discrete Fourier Transform (DFT)

$$X(k) = \sum_{n=0}^{N-1} x(n) e^{-\frac{j2\pi nk}{N}}$$

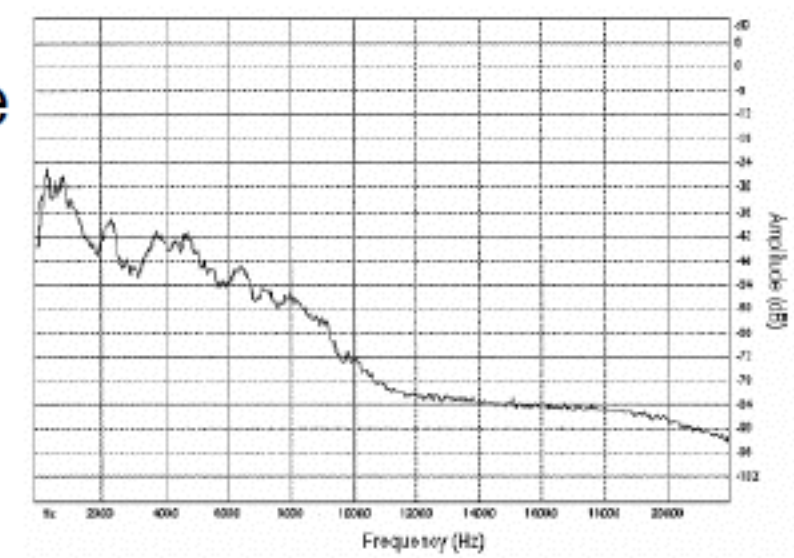
Inverse Discrete Fourier Transform (IDFT)

$$x(n) = \frac{1}{N} \sum_{n=0}^{N-1} X(k) e^{\frac{j2\pi nk}{N}}$$

- For large value of N, the signal is often broken into blocks called frames and DFT is applied to each of the frames.

Frequency-Domain Features (2)

- Bandwidth
  - indicated the frequency range of a sound
  - can be taken as the difference between the highest frequency and lowest frequency of non-zero spectrum components
  - “non-zero” may be defined as at least 3dB above the silence level



- Energy distribution
  - Signal distribution across frequency components
  - One important feature derived from the energy distribution is the *centroid*, which is the mid-point of the spectral energy distribution of a sound. Centroid is also called *brightness*

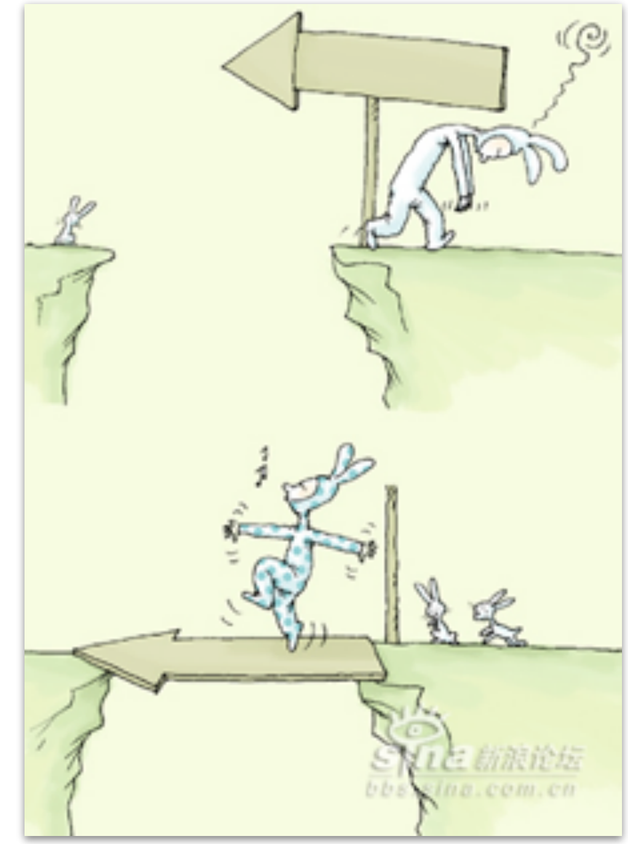
Frequency-Domain Features (3)

- Harmonicity
  - In harmonic sound, the spectral components are mostly whole number multiples of the lowest and most often loudest frequency
  - Lowest frequency is called *fundamental frequency*
  - Music is normally more harmonic than other sounds
- Pitch
  - the distinctive quality of a sound, dependent primarily on the frequency of the sound waves produced by its source
  - only period sounds, such as those produced by musical instruments and the voice, give rise to a sensation of a pitch
  - In practice, we use the fundamental frequency as the approximation of the pitch

相關研究

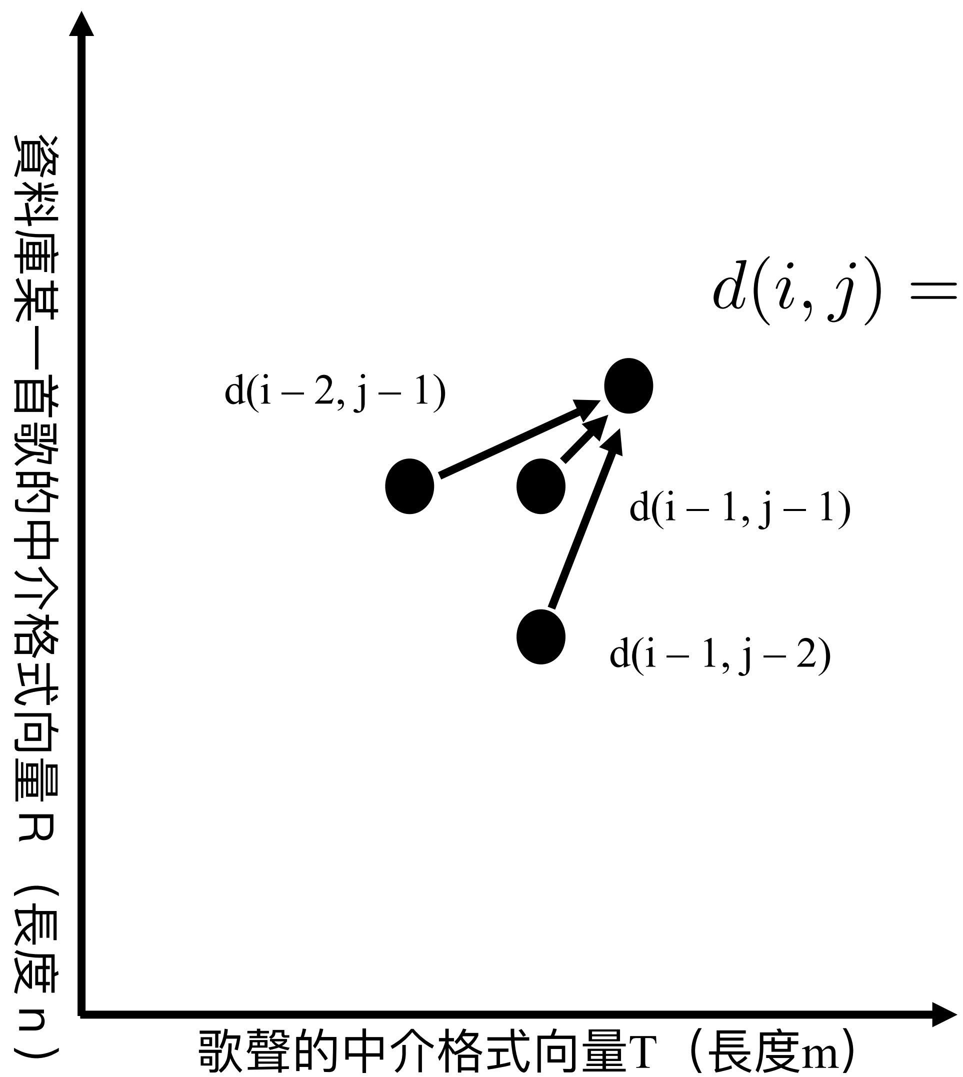
名稱	使用限制	比對方法	資料庫歌曲數目
Query by Humming	必須唱 ta 或 da 斷音	Baeza-Yates & Perleberg (92)	183
MELDEX (Melody Indexing)	必須唱 ta 或 da 斷音	Dynamic programming	9400
SoundCompass	必須照節拍器唱	Pitch transitions & histograms for weighted average	10086
MELODISCOV	無	FIExPat, Rolland (99)	未知

前人的方法



- 克服節奏快慢不同的問題
  - Dynamic time warping
- 克服音調高低不同的問題
  - Key transposition
    - 將使用者的歌聲和資料庫中的歌轉換後的中介格式的平均值都平移到0，做一次dtw比對
    - 將資料庫中的歌的中介格式上下平移再做四次dtw比對，以找出最短的距離
- 全曲比對費時很久且準確率低
- 使用浮點數運算

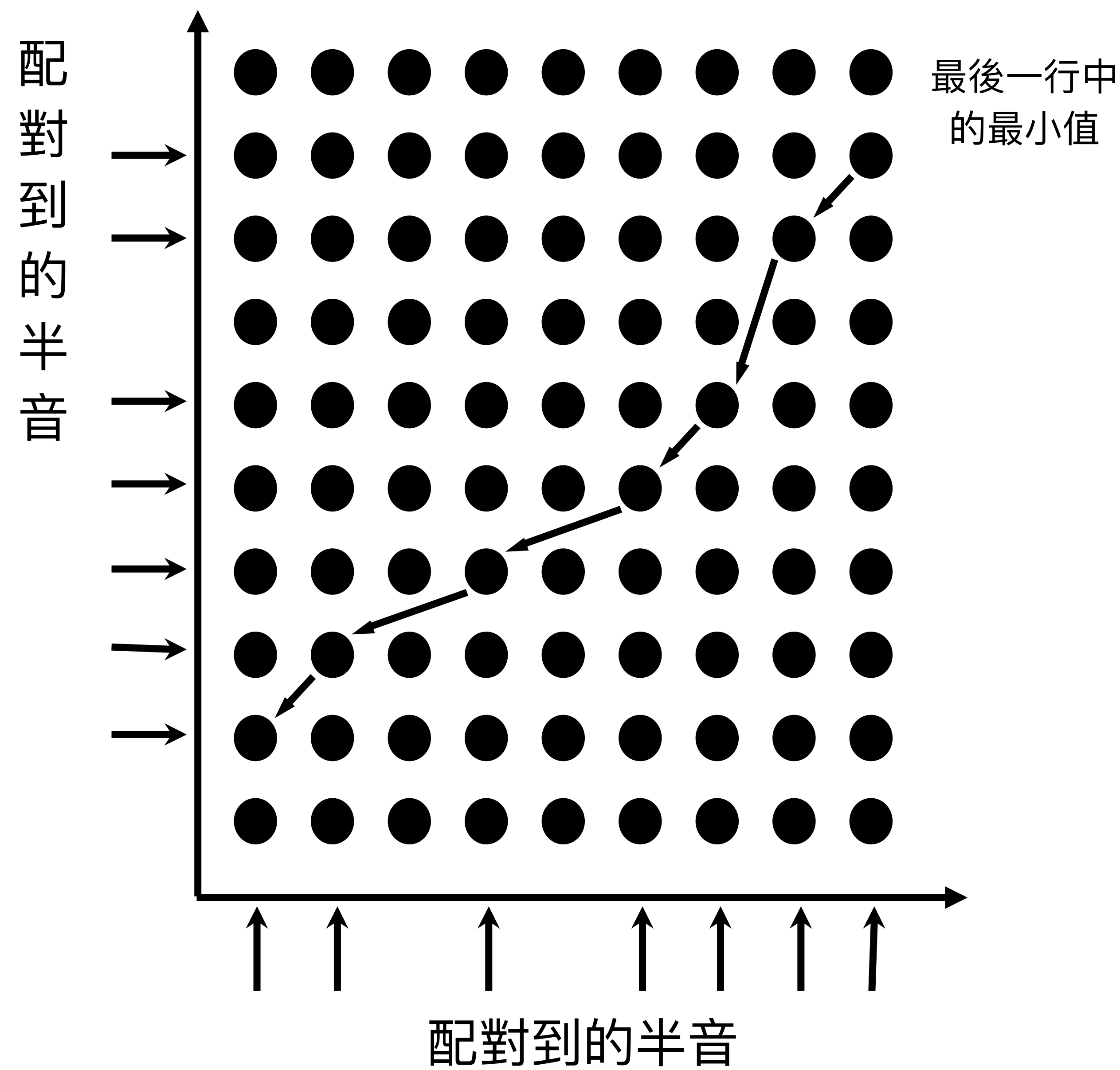
Dynamic Time Warping



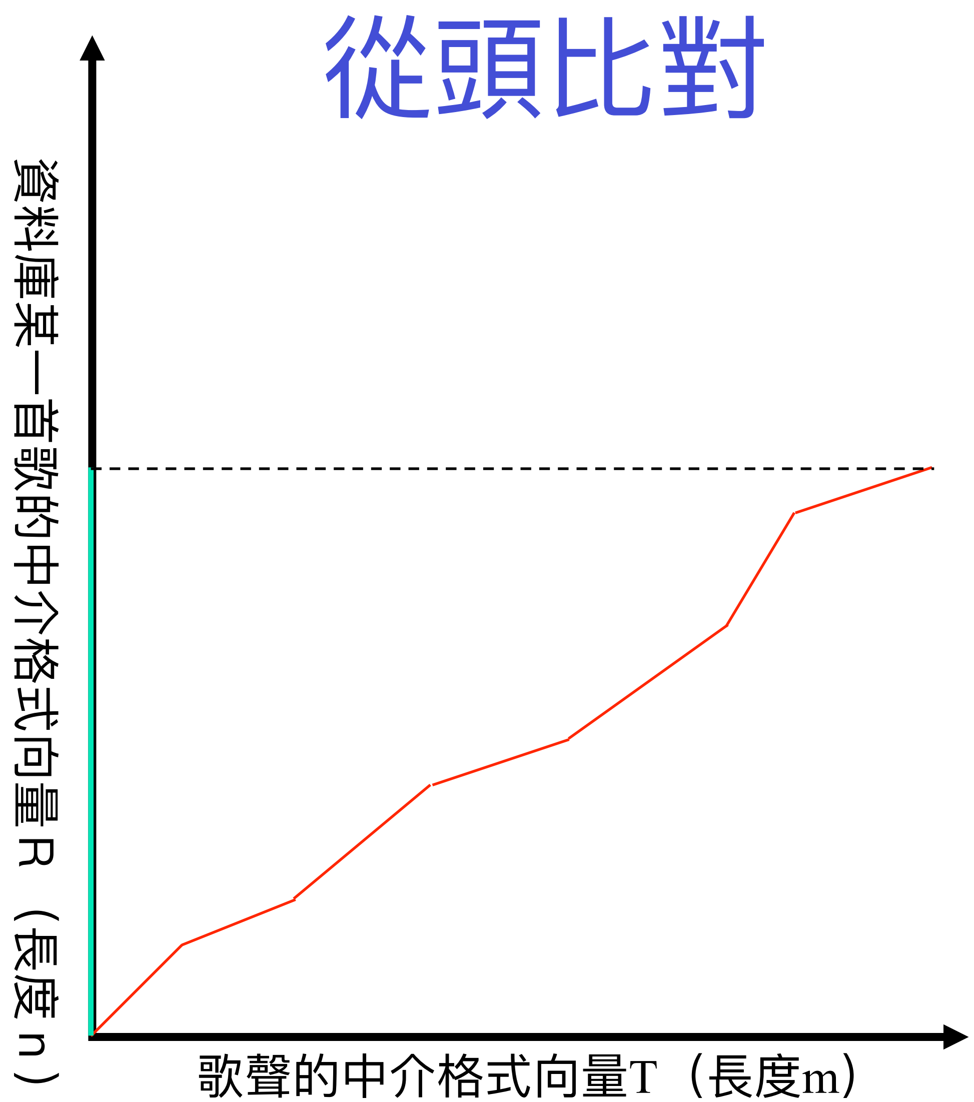
$$d(i,j) = \min \begin{cases} d(i-1, j-1) \\ d(i-2, j-1) + |T(i) - R(j)| \\ d(i-1, j-2) \end{cases}$$

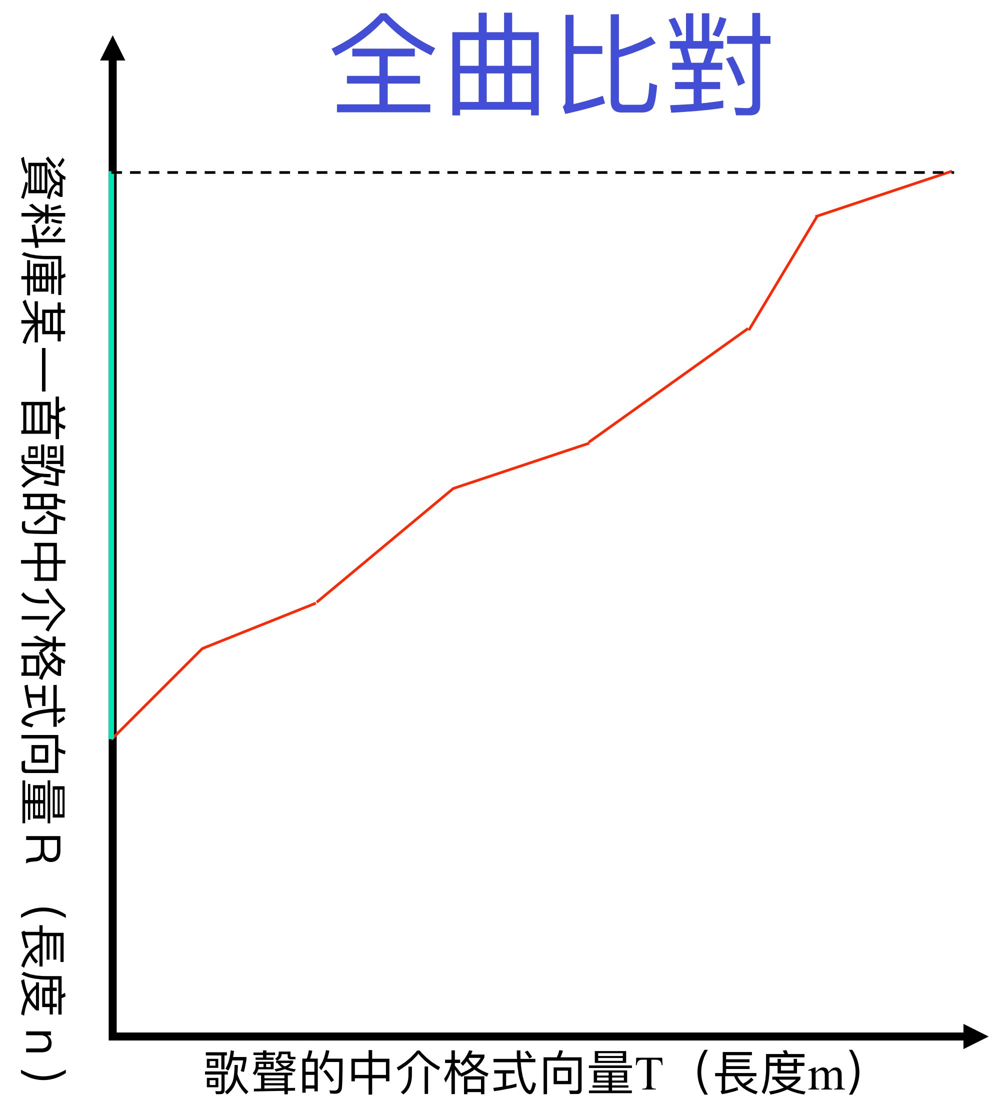
$$dtw(T,R) = \min_{1 \le j \le n} d(m, j)$$

Dynamic Time Warping



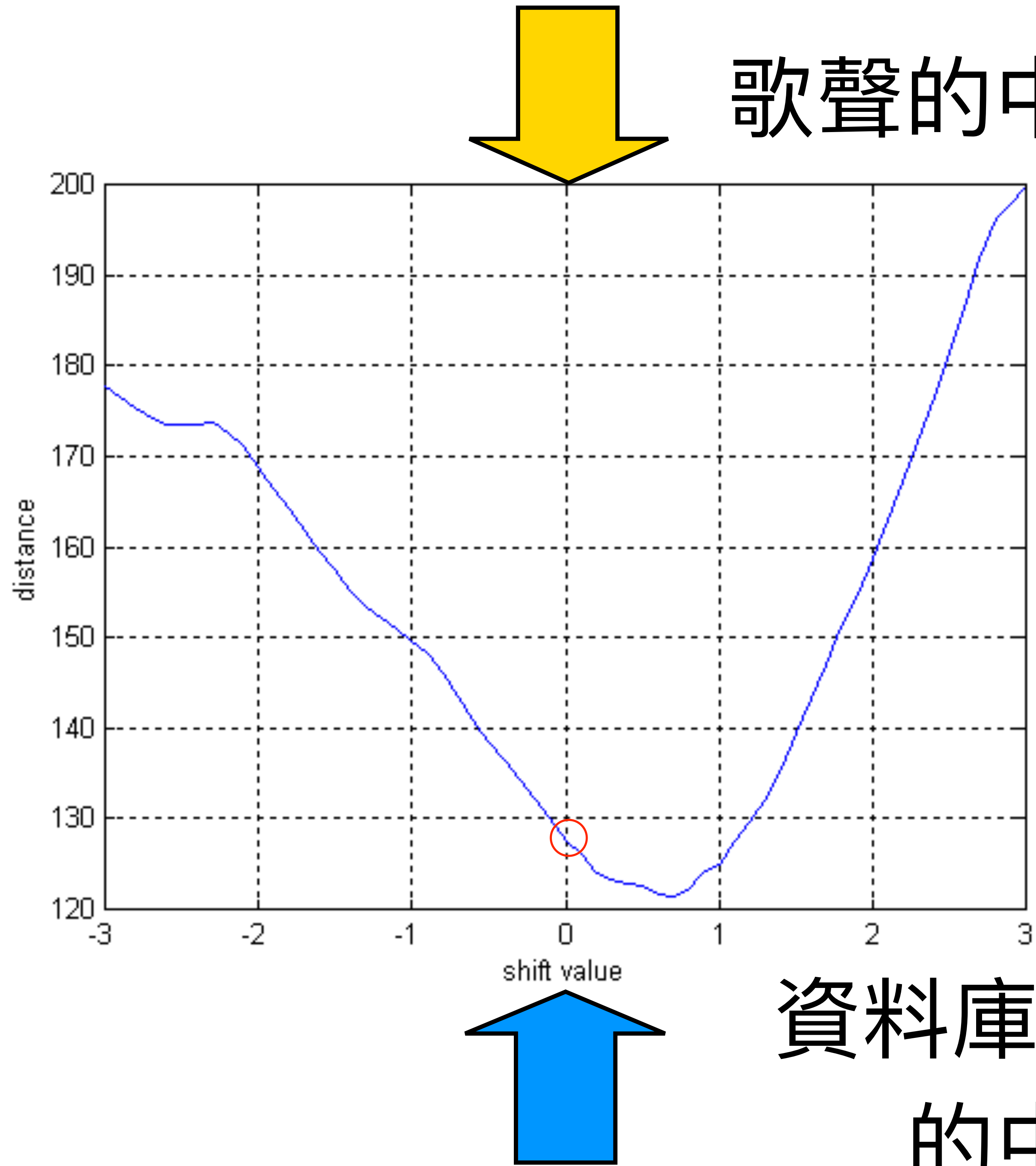
Dynamic Time Warping





Key Transposition

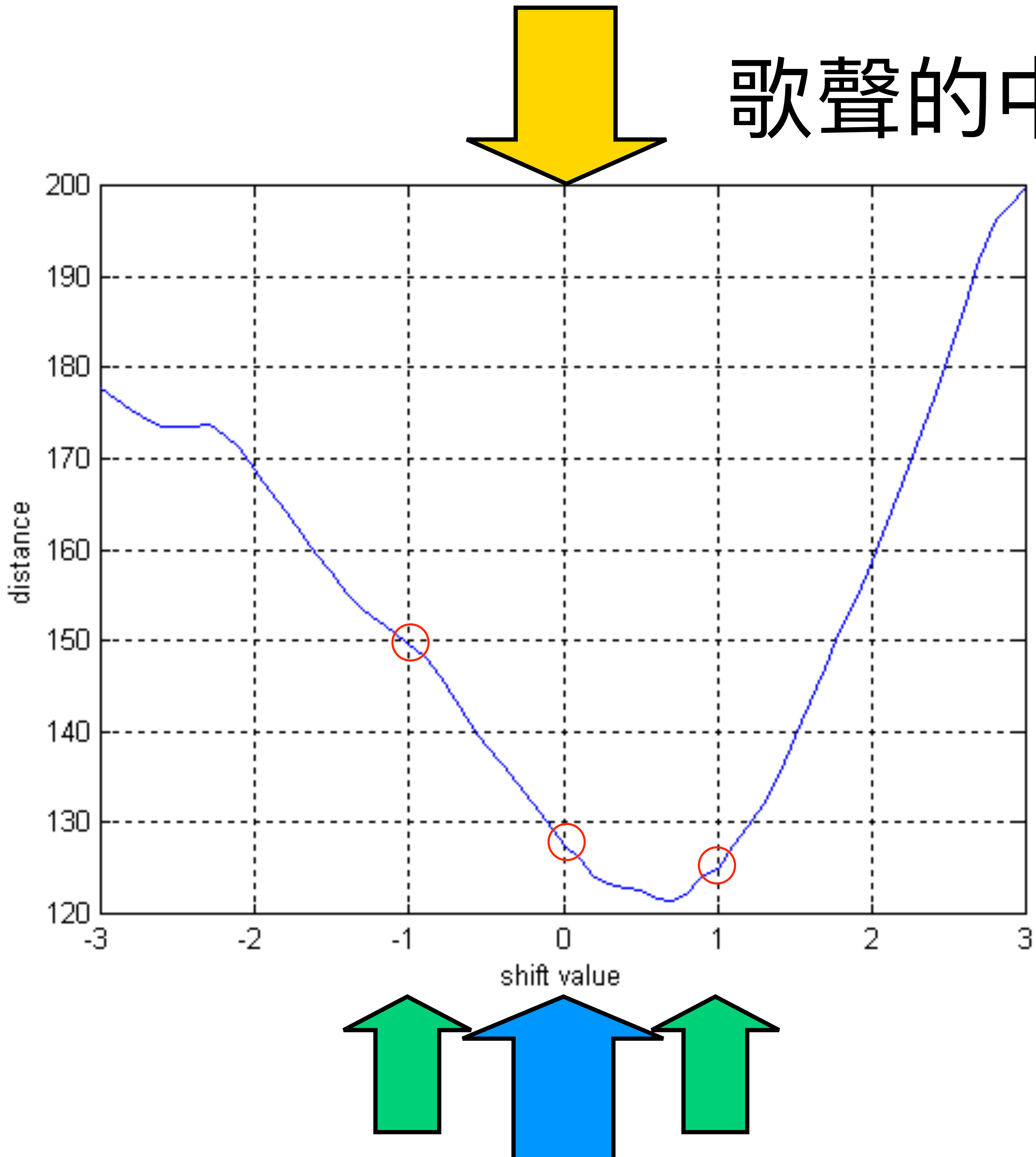
歌聲的中介格式



資料庫中某一首歌
的中介格式

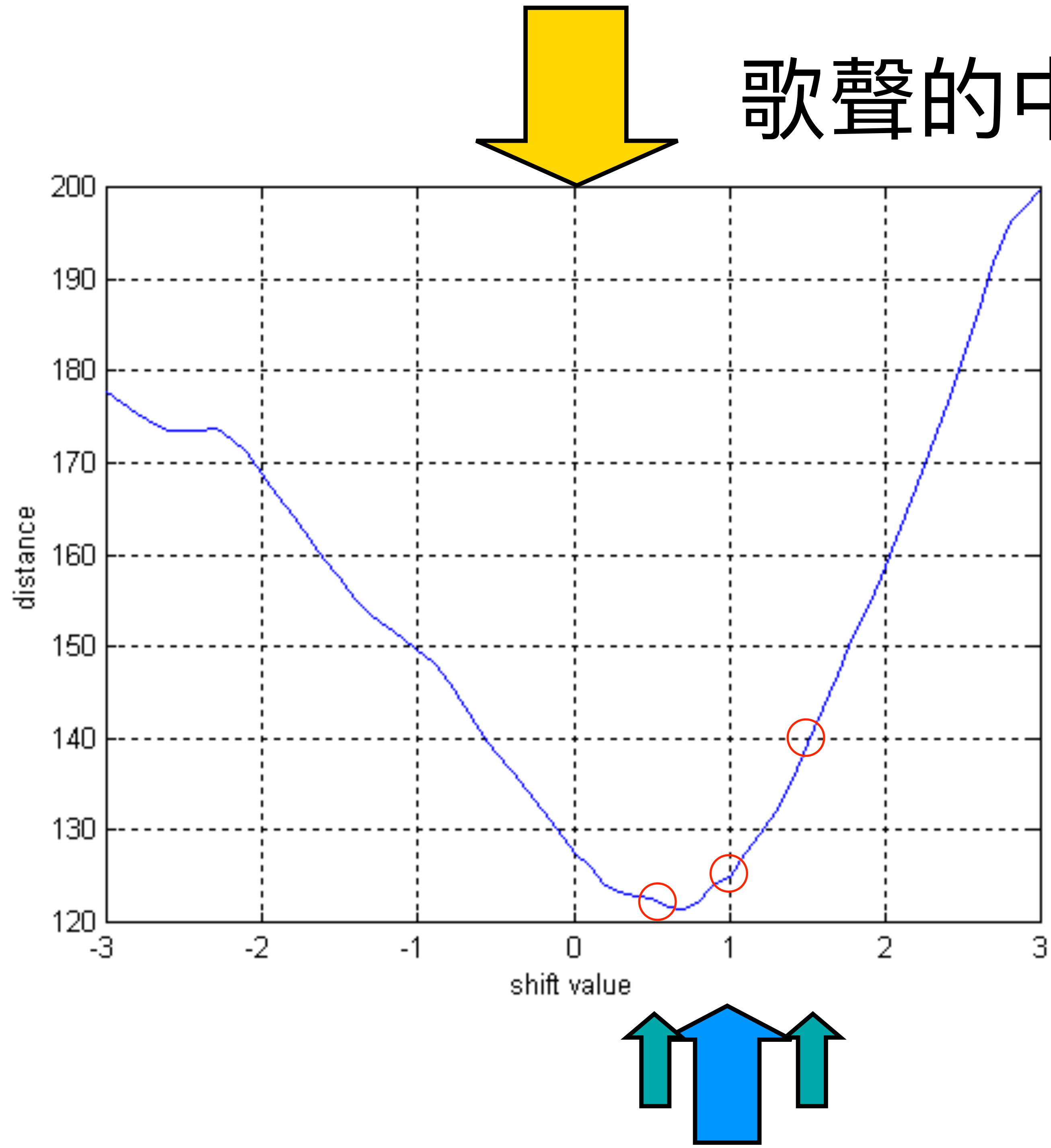
Key Transposition

歌聲的中介格式



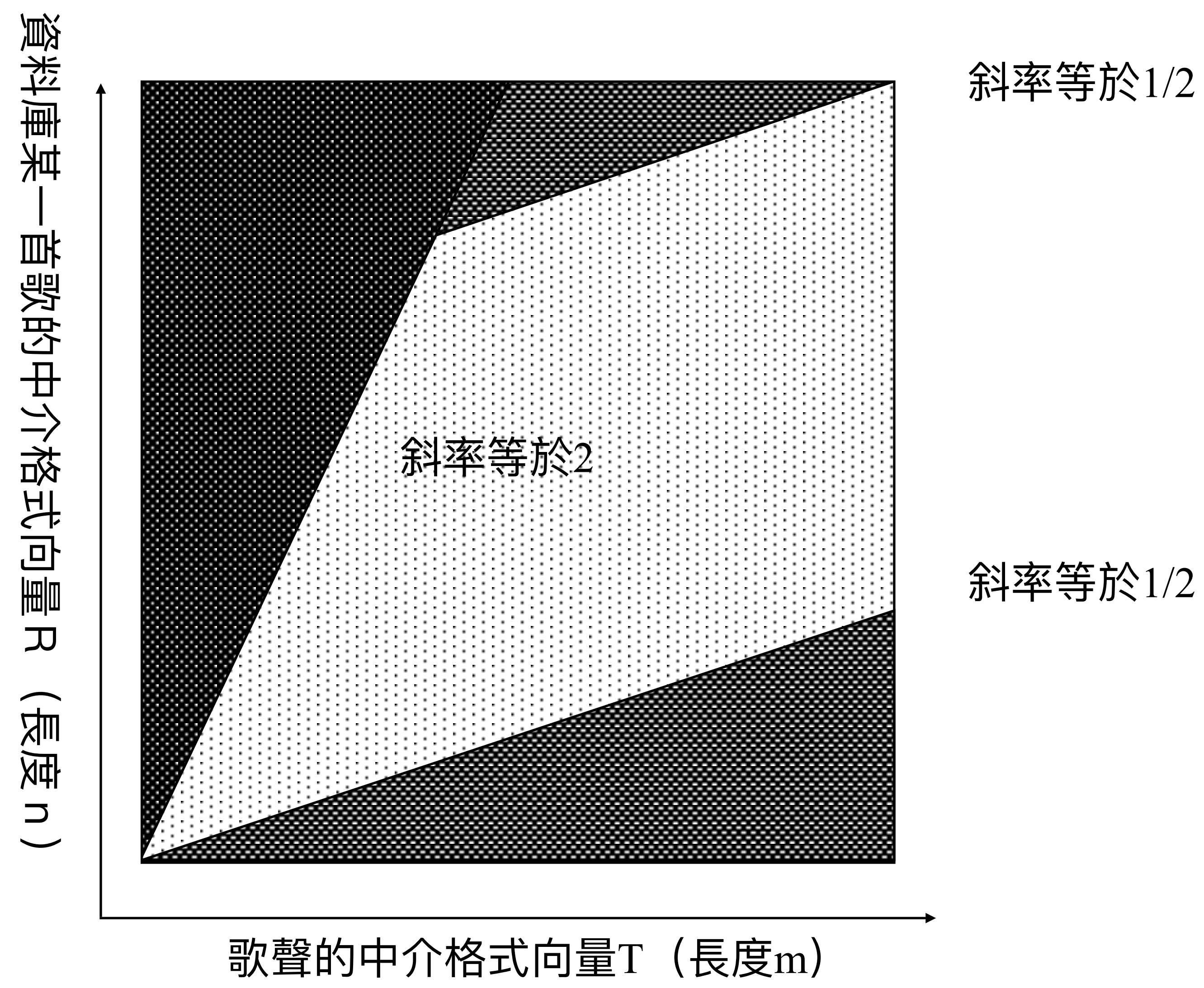
Key Transposition

歌聲的中介格式



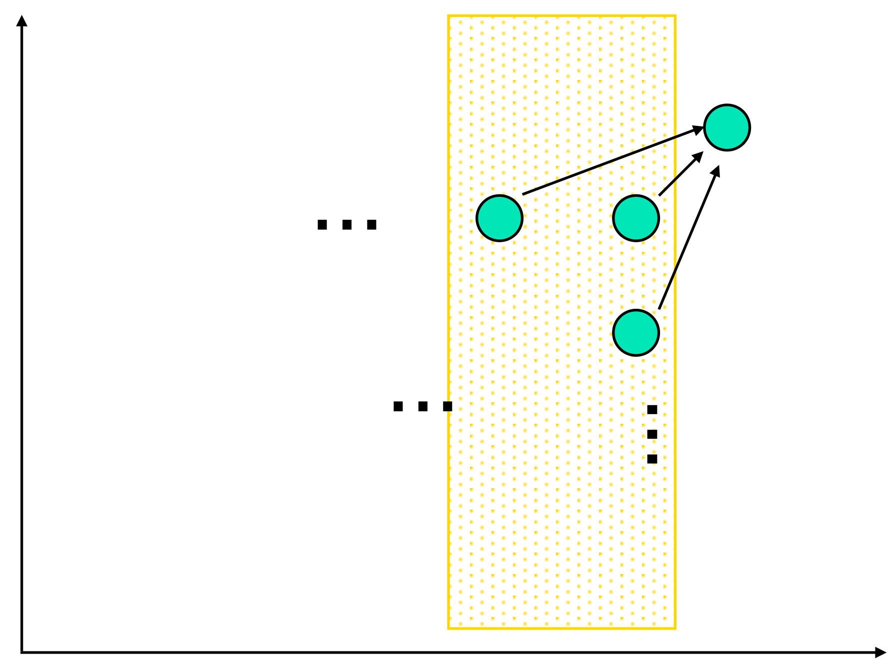
改進方法一

- 改用整數運算
  - 犧牲部分准确率
- 改良式dtw
  - 因為T的頭尾必須match到R的某一段，所以顏色較深的地方不必計算



改進方法一

- 改良式dtw
  - 用dtw計算每一首歌的距離時，若發現dtw table最近兩行(column)的最小值超過之前最短距離的前k名，則停止dtw



改進方法二

- 將資料庫中每一首歌的中介格式，從每一個音符為起點切成數個長度為 D=72 的片段

中介格式　(<u>69</u>, 69, <u>67</u>, 67, 67, <u>71</u>, <u>72</u>, ……)

→　片段1　(69, 69, 67, 67, 67, 71, 72, …)

片段2　(67, 67, 67, 71, 72, …)

片段3　(71, 72, …)

……

改進方法二

- 用兩階段的方法比對
  - 第一階段：線性伸縮比對（linear scaling）
    - 將歌聲的中介格式伸縮11次（長度為原來的0.75倍到1.25倍），分別取出前 D 點後為 T_i（$1 \leqq i \leqq 11$），假設資料庫中的第 j 首歌的中介格式有 n_j 個片段為 R_{jk}（$1 \leqq j \leqq$ 資料庫中的歌曲數目，$1 \leqq k \leqq n_j$），令 T_i 和 R_{jk} 的距離為

$$dist(T_i, R_{jk}) = \sqrt{\sum_{t=1}^{D} \left(\left(T_{it} - \overline{T_i}\right) - \left(R_{jkt} - \overline{R_{jk}}\right) \right)^2}$$

改進方法二

- 令資料庫第 j 首歌的分數為 $100 - \min\limits_{\substack{1 \le i \le 11 \\ 1 \le k \le n_j}} \frac{dist(T_i, R_{jk})}{D}$，令

  $$k' = \arg\min_{\substack{1 \le i \le 11 \\ 1 \le k \le n_j}} dist(T_i, R_{jk})$$

- 篩選出前 n=200 首分數最高者做第二階段的比對
- 缺點：每和資料庫中第 j 首歌做比對就要計算n_j*11次距離

- 第二階段：dynamic time warping
  - 將篩選後的每一首歌的最接近片段平移音調4次，總共和歌聲原本的中介格式計算5次距離，找出最小值並轉換成分數，當成資料庫該首歌最後的分數

針對全曲比對的加速方法

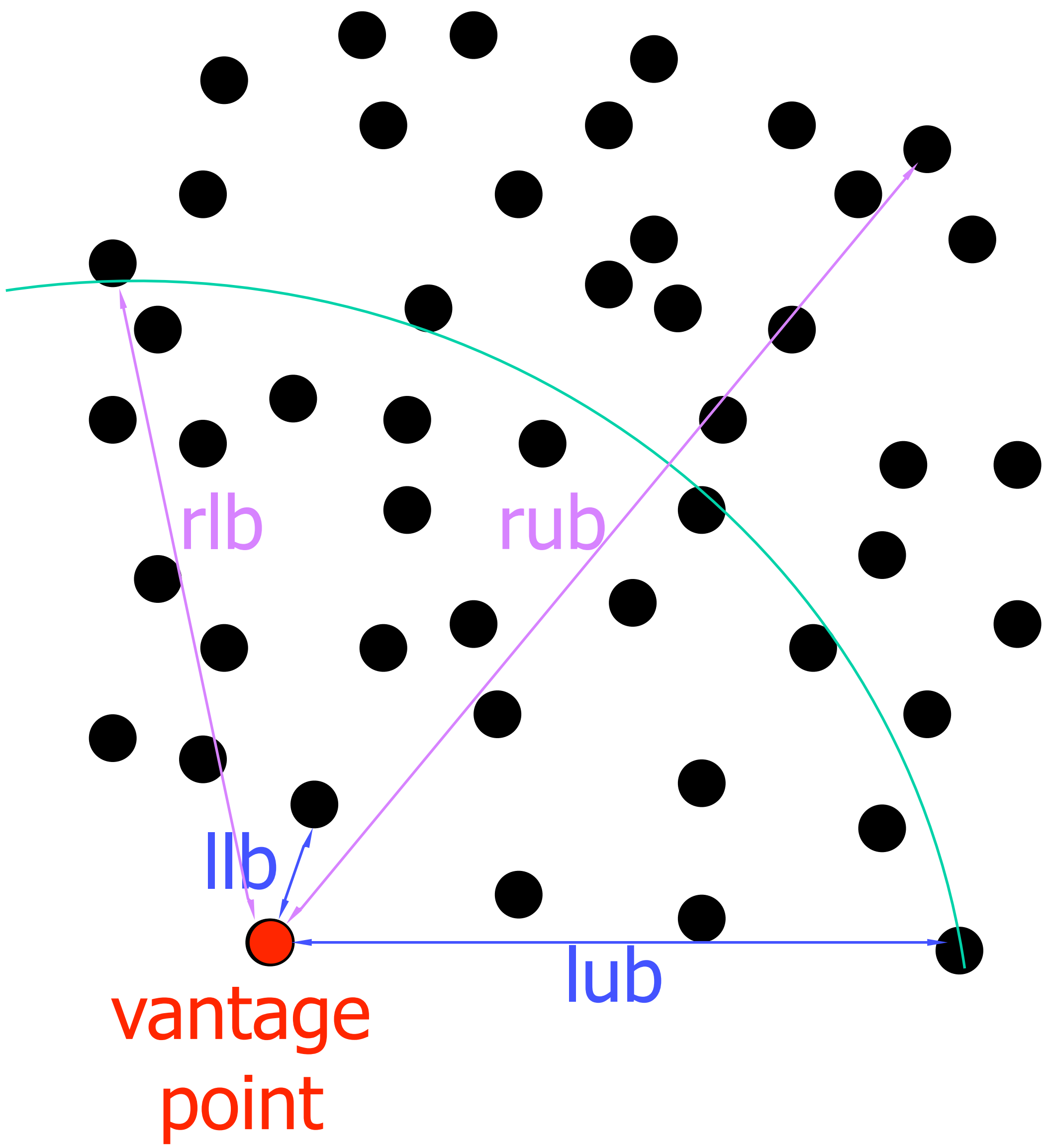
- 用兩階段式比對
- 在第一階段將資料庫歌曲的每一個片段看成一個 D 度空間中的資料點，歌聲伸縮後的中介格式則是空間中的查詢點，利用快速找最近鄰居的方法找出每首歌最接近的片段
  - Vantage-point tree
  - Branch-and-bound tree
  - Equal-average hyperplane partitioning method

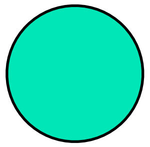
Vantage-Point Tree

- 將資料點建立成一個平衡的二叉树，利用距離滿足三角不等式的關係，可以減少計算查詢點到資料點的距離的次數
  - 缺點：建樹麻煩，使用時耗記憶體
  - 困難：資料點少，查詢點到所有資料點的距離都差不多，加速效果不顯著

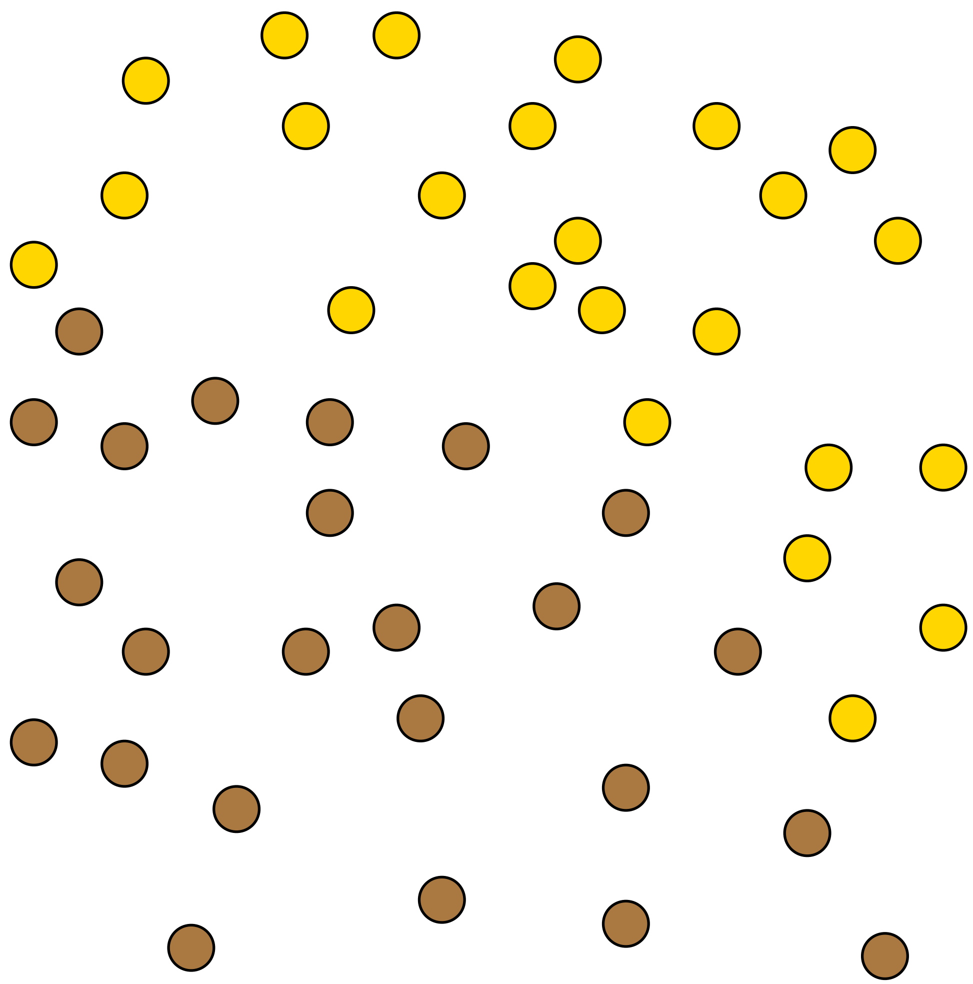
Vantage-Point Tree

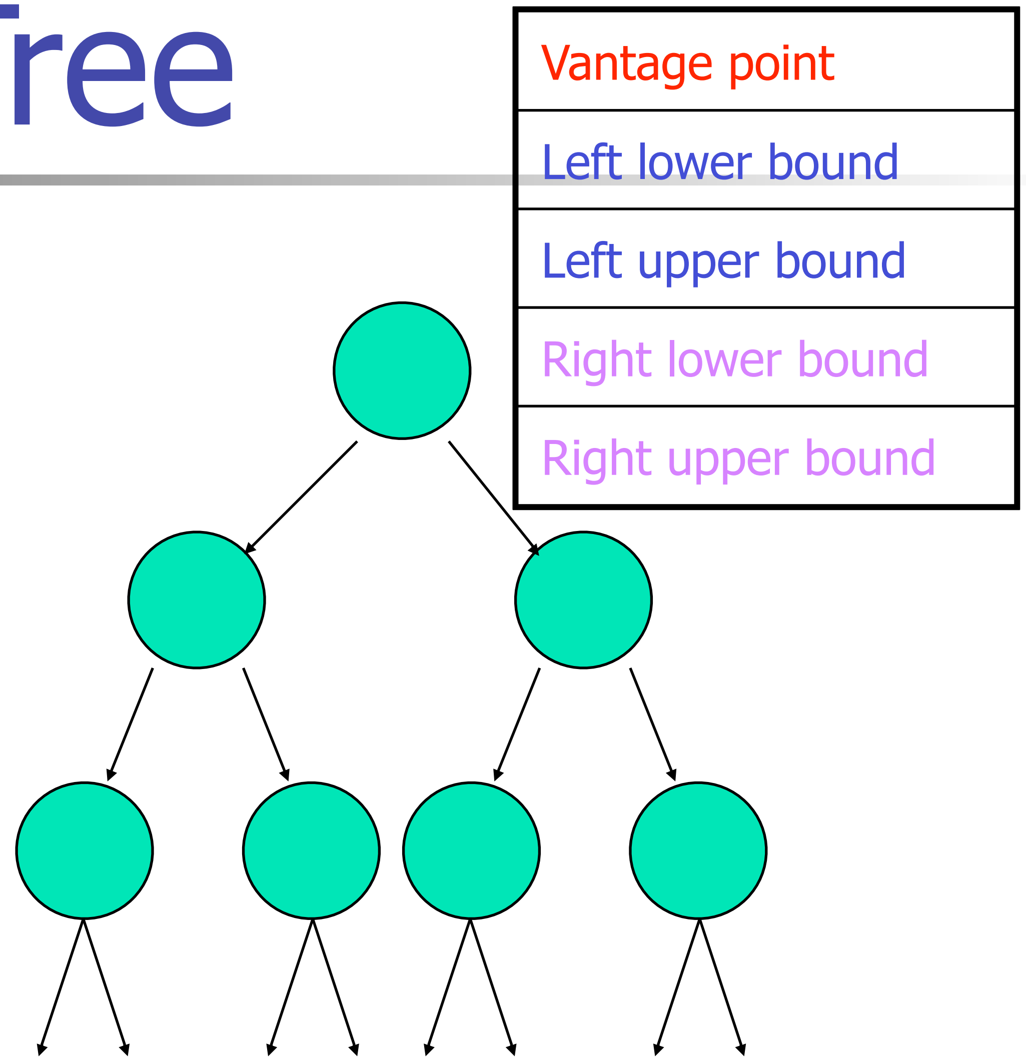
Vantage point
Left lower bound
Left upper bound
Right lower bound
Right upper bound

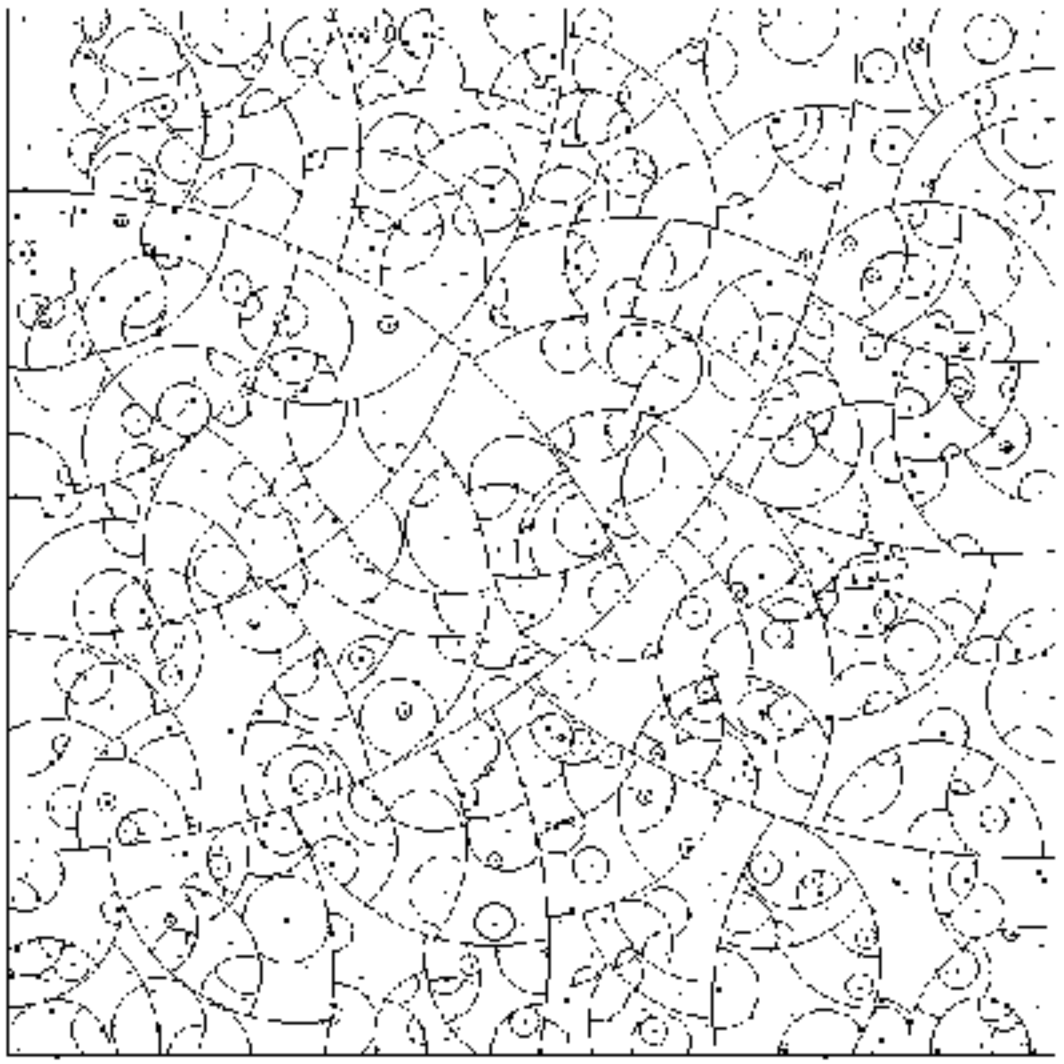




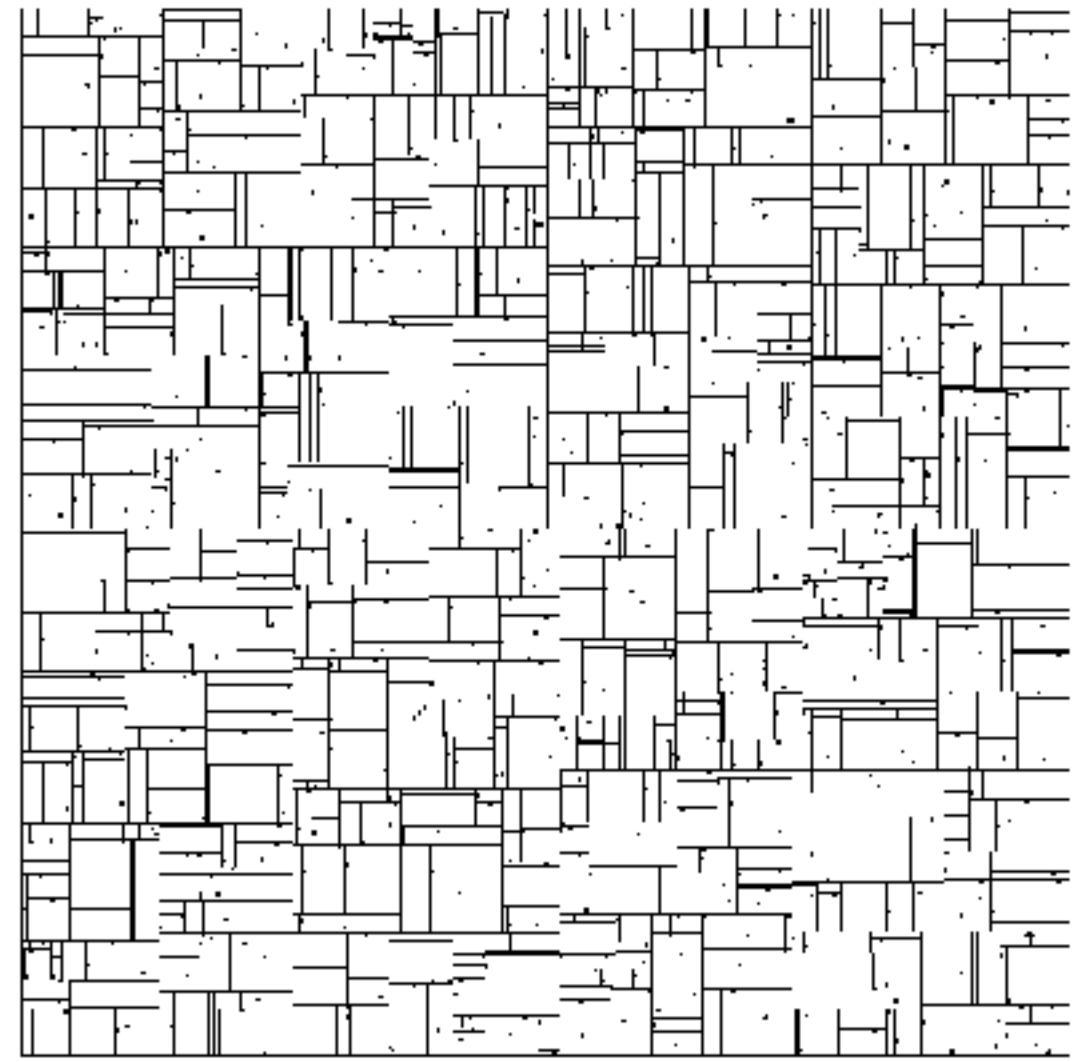
Vantage-Point Tree







VP-tree decomposition

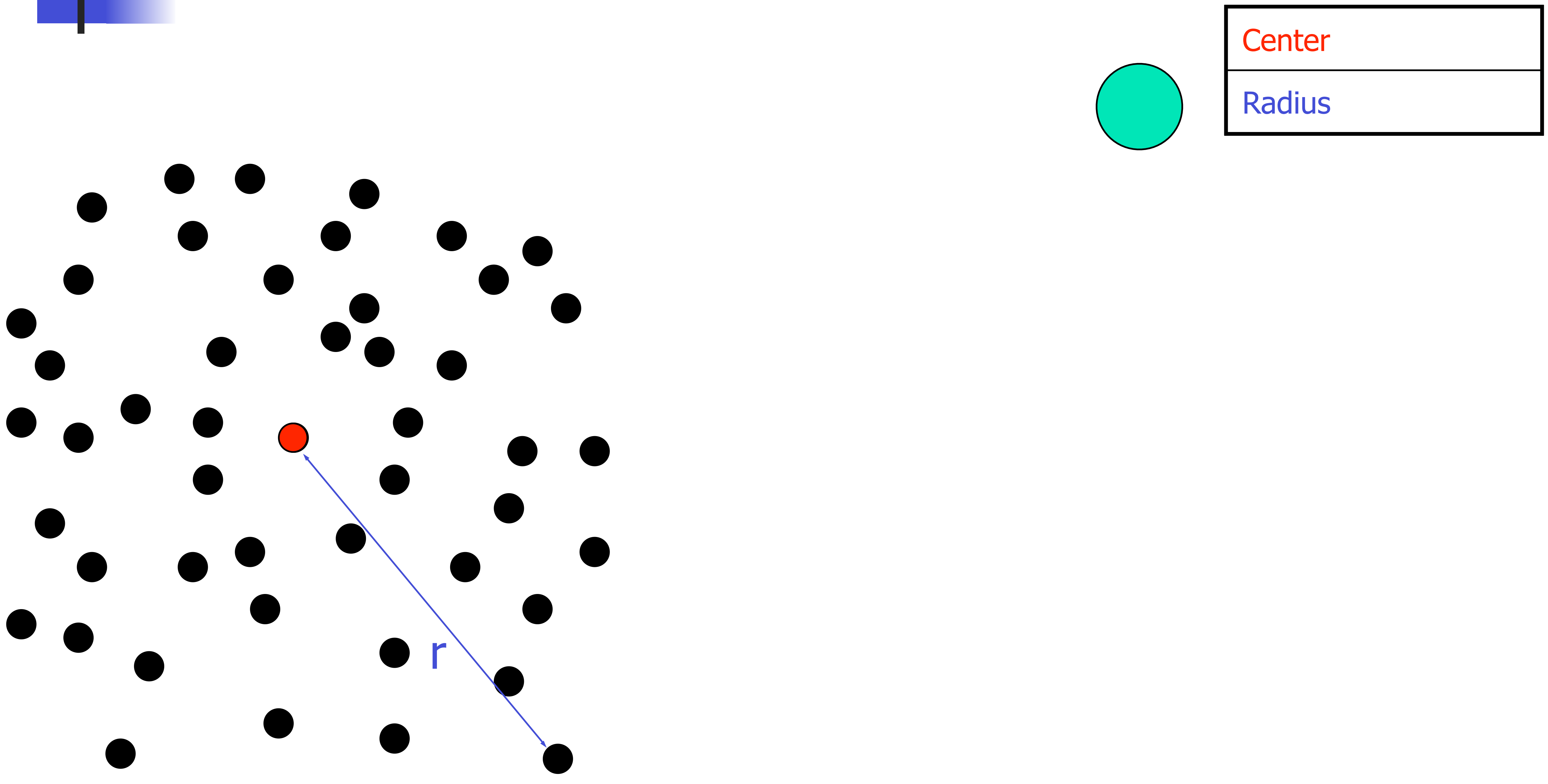


KD-tree decomposition

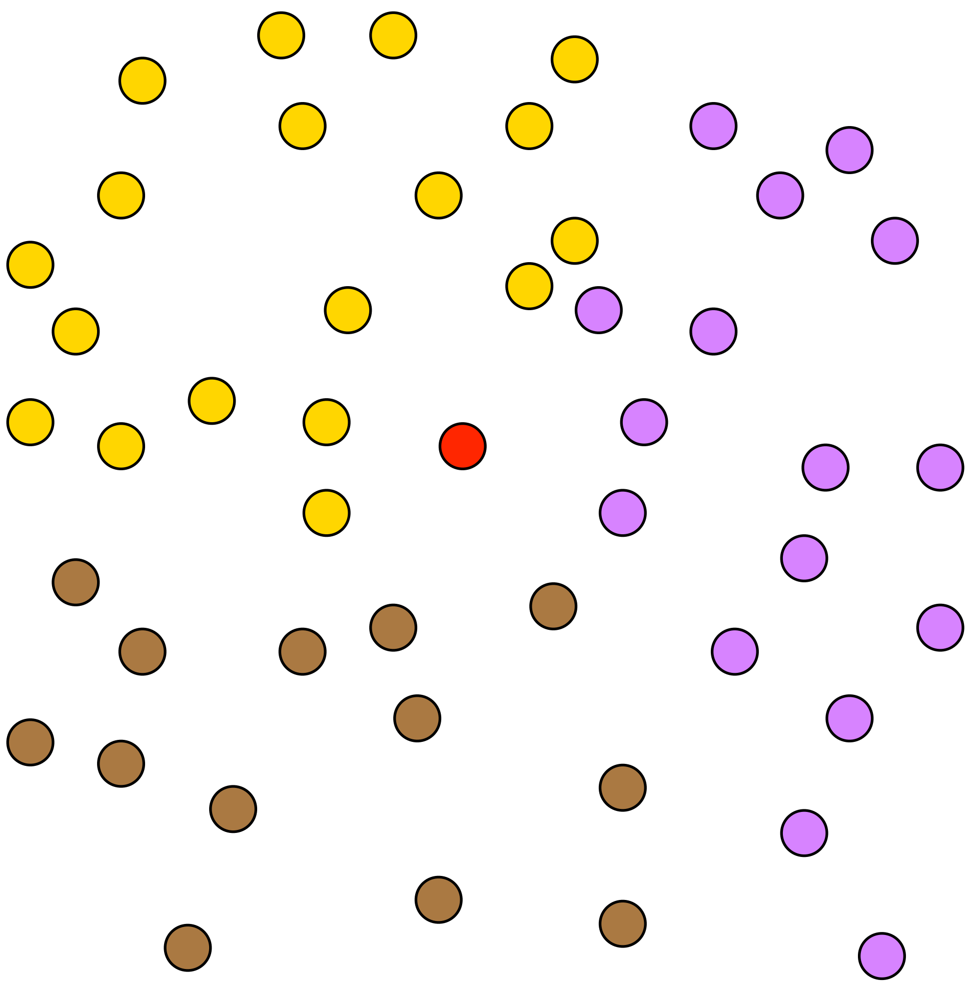
Branch-and-Bound Tree

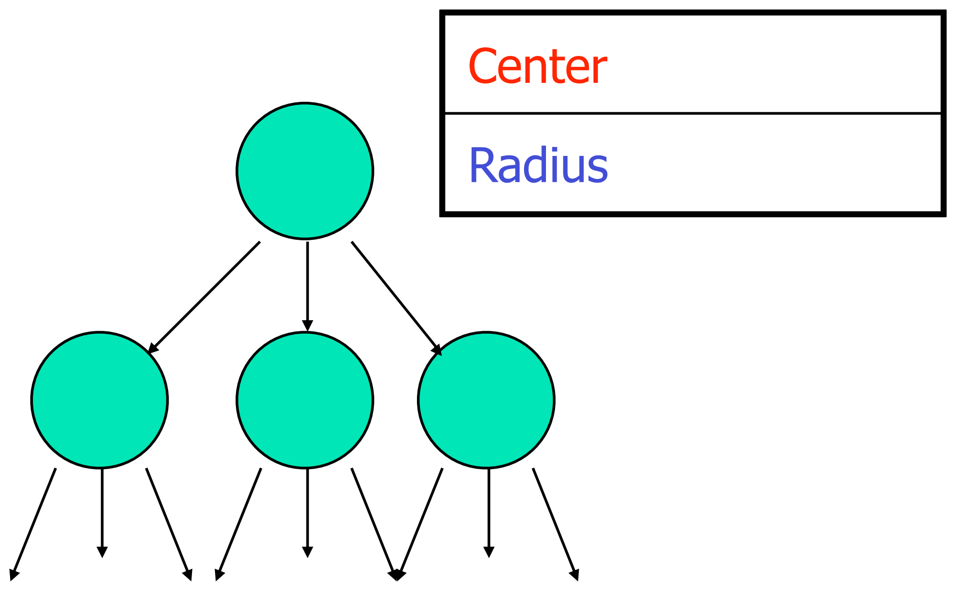
- 原理類似vantage-point tree，將資料點建立成一個多元樹，利用距離滿足三角不等式的關係，可以減少計算查詢點到資料點的距離的次數
  - 缺點：建樹時使用K-means，麻煩耗時，使用時耗記憶體
  - 困難：資料點少，查詢點到所有資料點的距離都差不多，加速效果不顯著

Branch-and-Bound Tree



Branch-and-Bound Tree



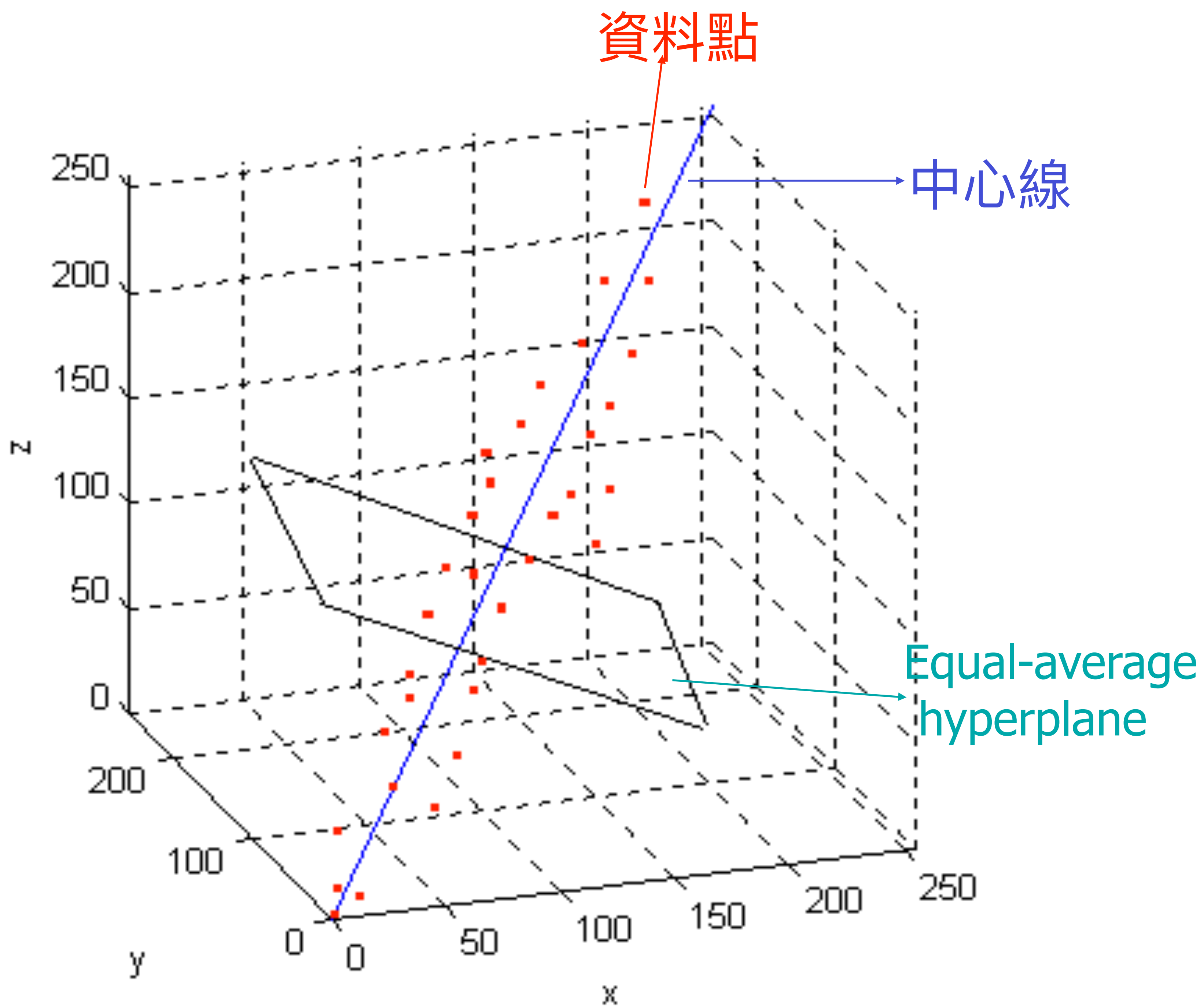


Equal-average Hyperplane Partitioning Method

- 讓資料點沿一直線分散開來，事先算出每一個資料點投影到直線上的位置。利用兩資料點間的距離會大於或等於這兩點投影到該直線上的距離的關係，可以減少計算查詢點到資料點的距離的次數
  - 優點：實作容易，省記憶體
  - 缺點：使用時機較狹隘

Equal-average Hyperplane Partitioning Method

- 中心線 L 是一條通過原點和 (1, 1, 1, …, 1) 的直線
- Equal-average hyperplane是和 L 垂直的面



Equal-average Hyperplane Partitioning Method

- 假設 a=(s, s, …, s) 為 L 上的一個點
- 則和 L 相交於 a 點的 equal-average hyperplane 其方程式為

$$H(x) = s\sum_{i=1}^{D} x_i - Ds^2 = 0$$

$$\Rightarrow s = \frac{1}{D}\sum_{i=1}^{D} x_i \leftarrow \text{座標平均值}$$

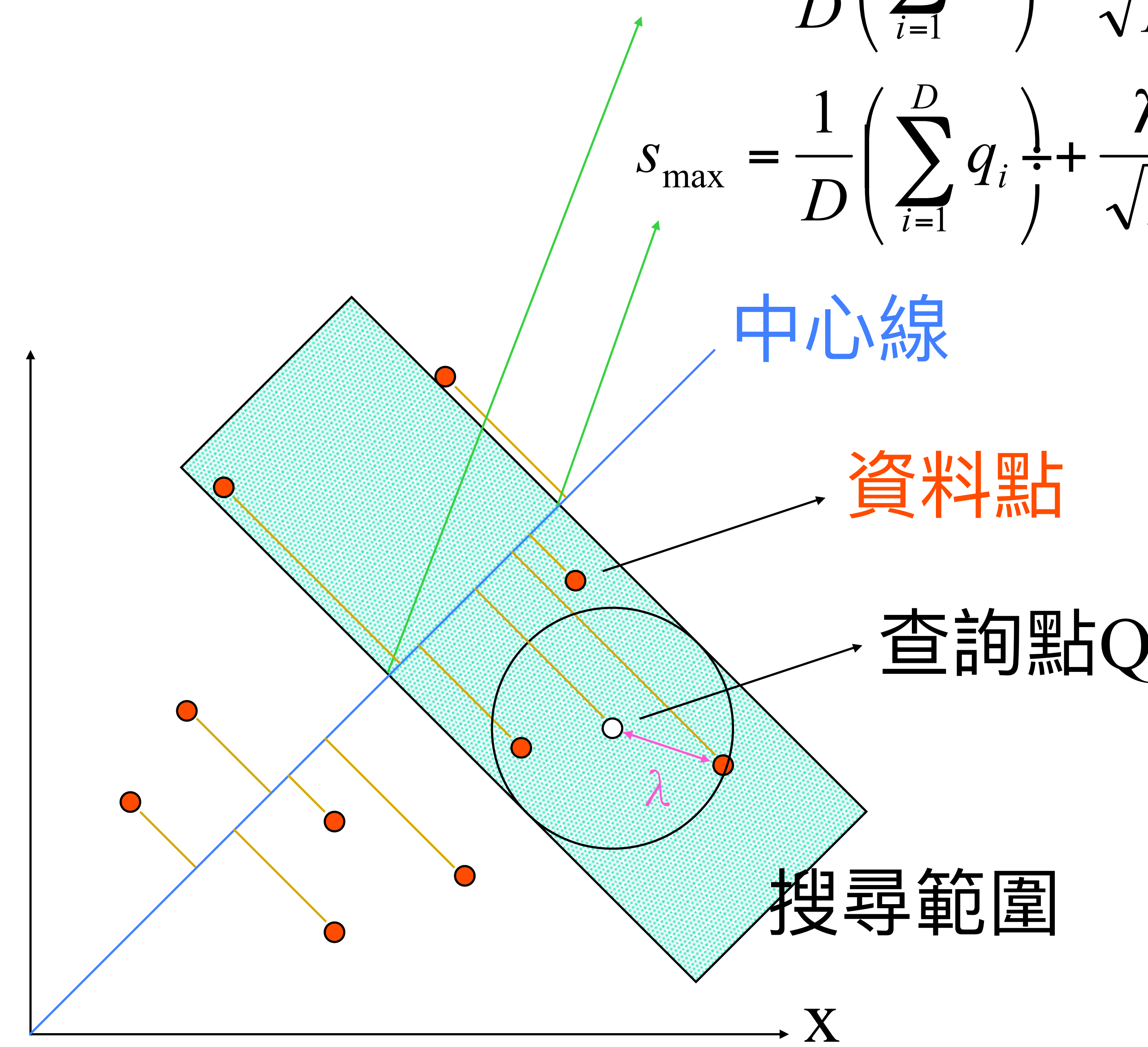
- 座標平均值相同的點會落在同一個equal-average hyperplane

Equal-average Hyperplane Partitioning Method

- 座標平均值落在 $[S_{min}, S_{max}]$之外的點不可能是最近鄰居

$$s_{\min} = \frac{1}{D}\left(\sum_{i=1}^{D} q_i\right) - \frac{\lambda}{\sqrt{D}}$$

$$s_{\max} = \frac{1}{D}\left(\sum_{i=1}^{D} q_i\right) + \frac{\lambda}{\sqrt{D}}$$

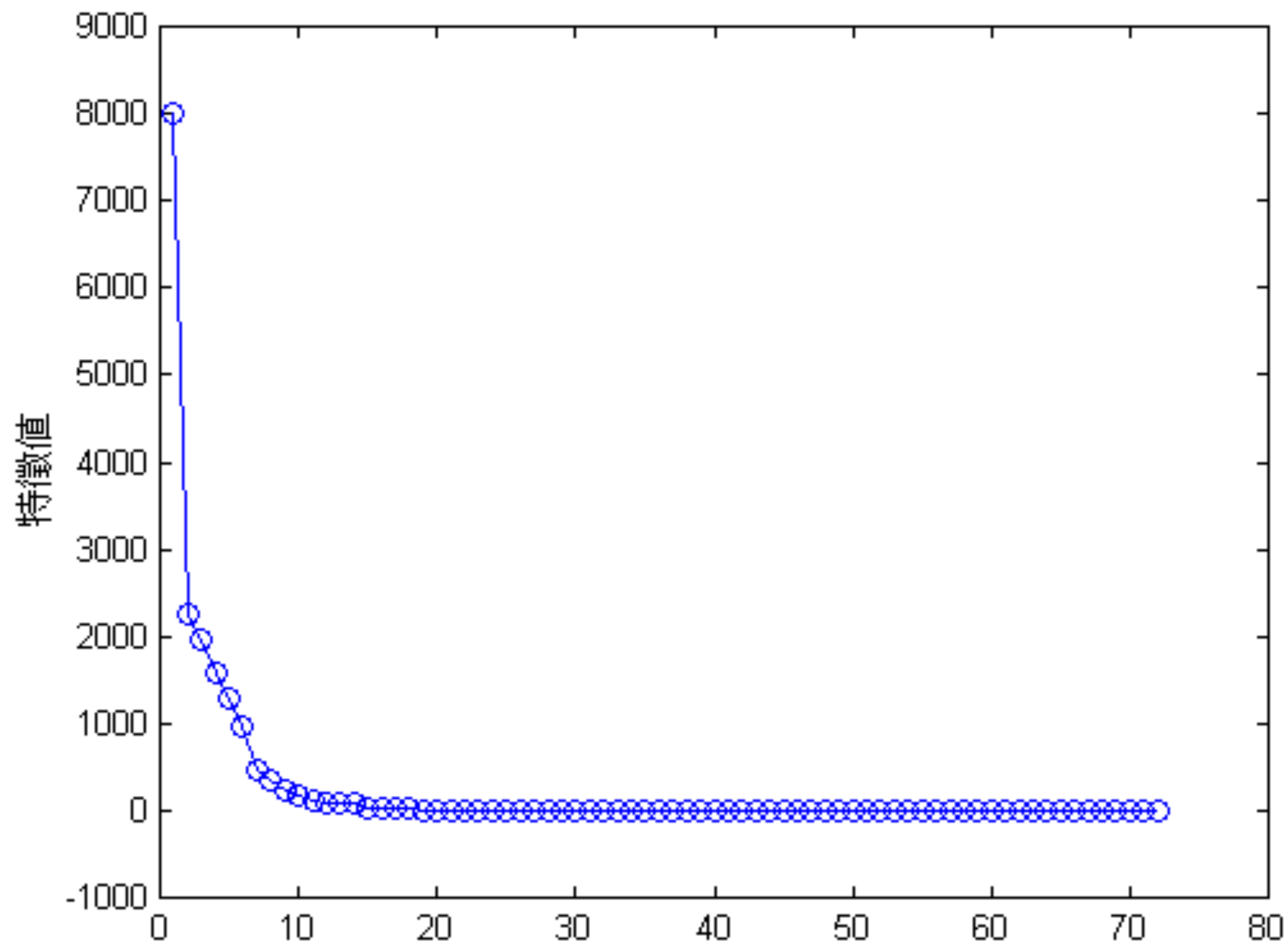


Equal-average Hyperplane Partitioning Method

- 因為我們將每個資料點平移到平均值為0，所以必須另外找一條直線 L 代替原本的中心線
  - 用 principal component analysis 找出 L
    - 令 M 矩陣的每一列為資料點R_{jk}的座標
    - 求出 $M^T M$ 的eigenvalue和eigenvector
    - 對應到最大eigenvalue的eigenvector即為所求
  - 用 $\frac{R_{jk} \times L}{\sqrt{D}}$ 代替座標平均值

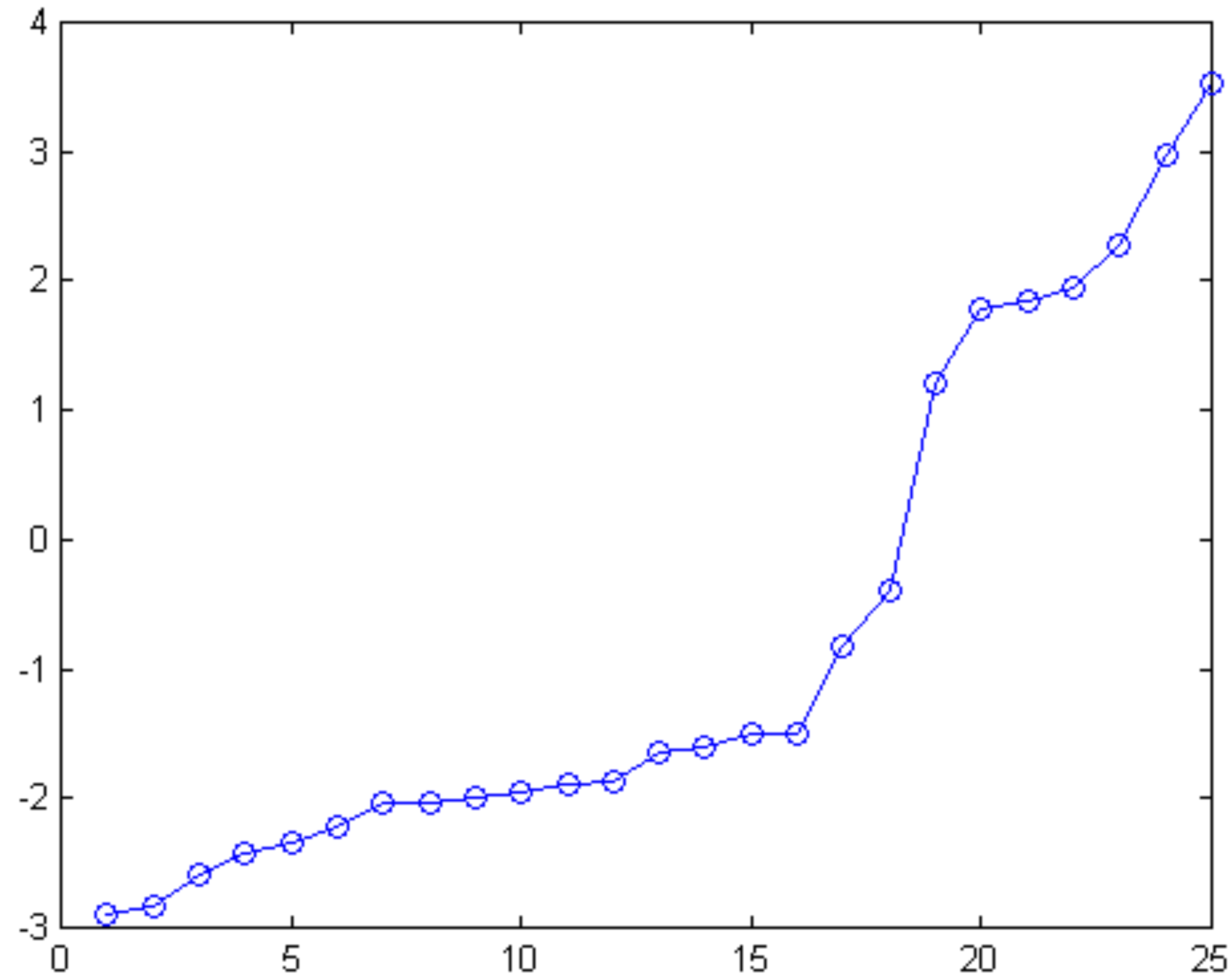
Equal-average Hyperplane Partitioning Method

- 資料庫中某一首歌曲有25個片段，每個片段長度為72
- 用PCA找出來的72個特徵值從大到小排序



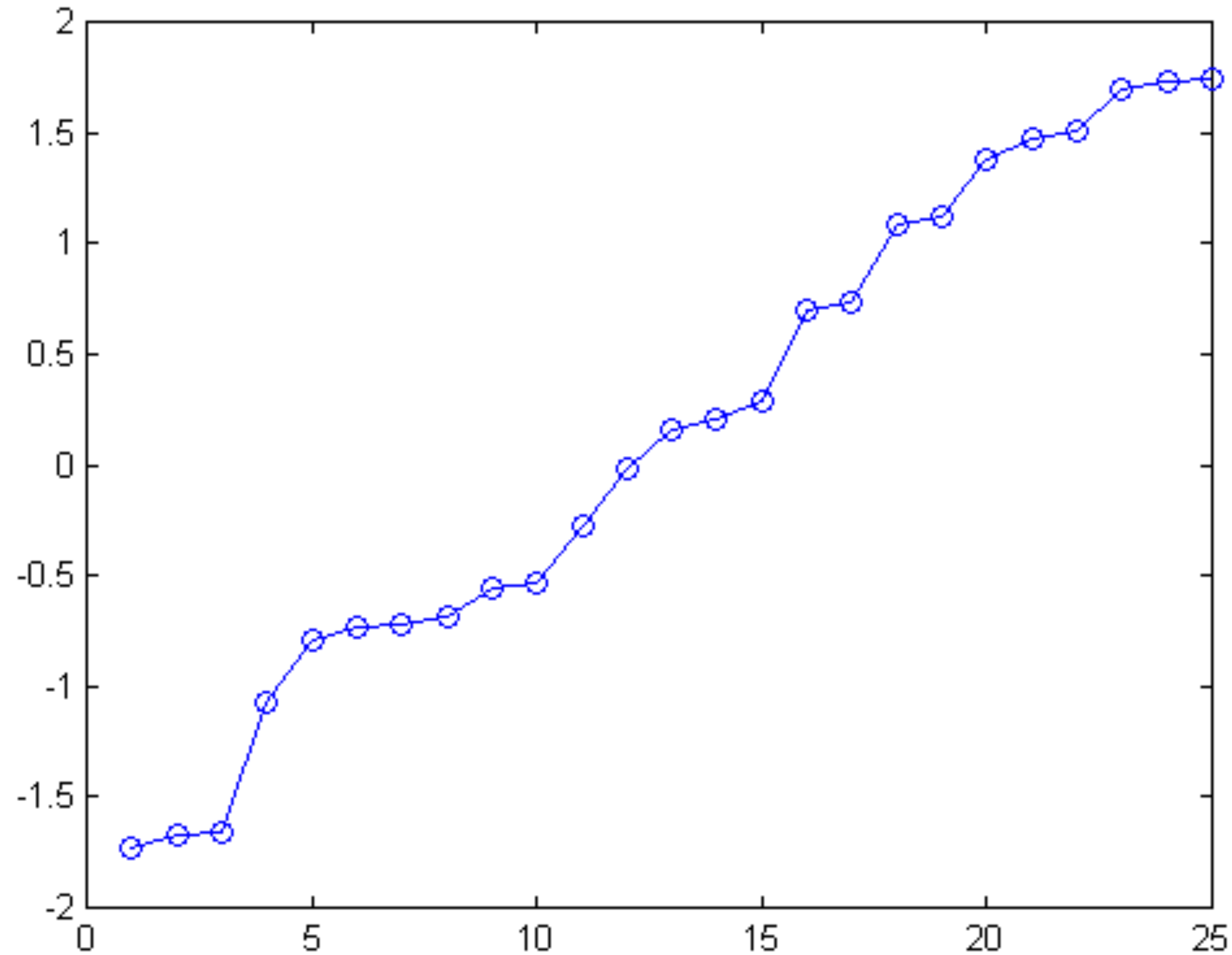
Equal-average Hyperplane Partitioning Method

- 25個片段投影在對應到最大特徵值的特徵向量後的座標平均值從小到大排序



Equal-average Hyperplane Partitioning Method

- 25個片段投影在對應到第二大特徵值的特徵向量後的座標平均值從小到大排序

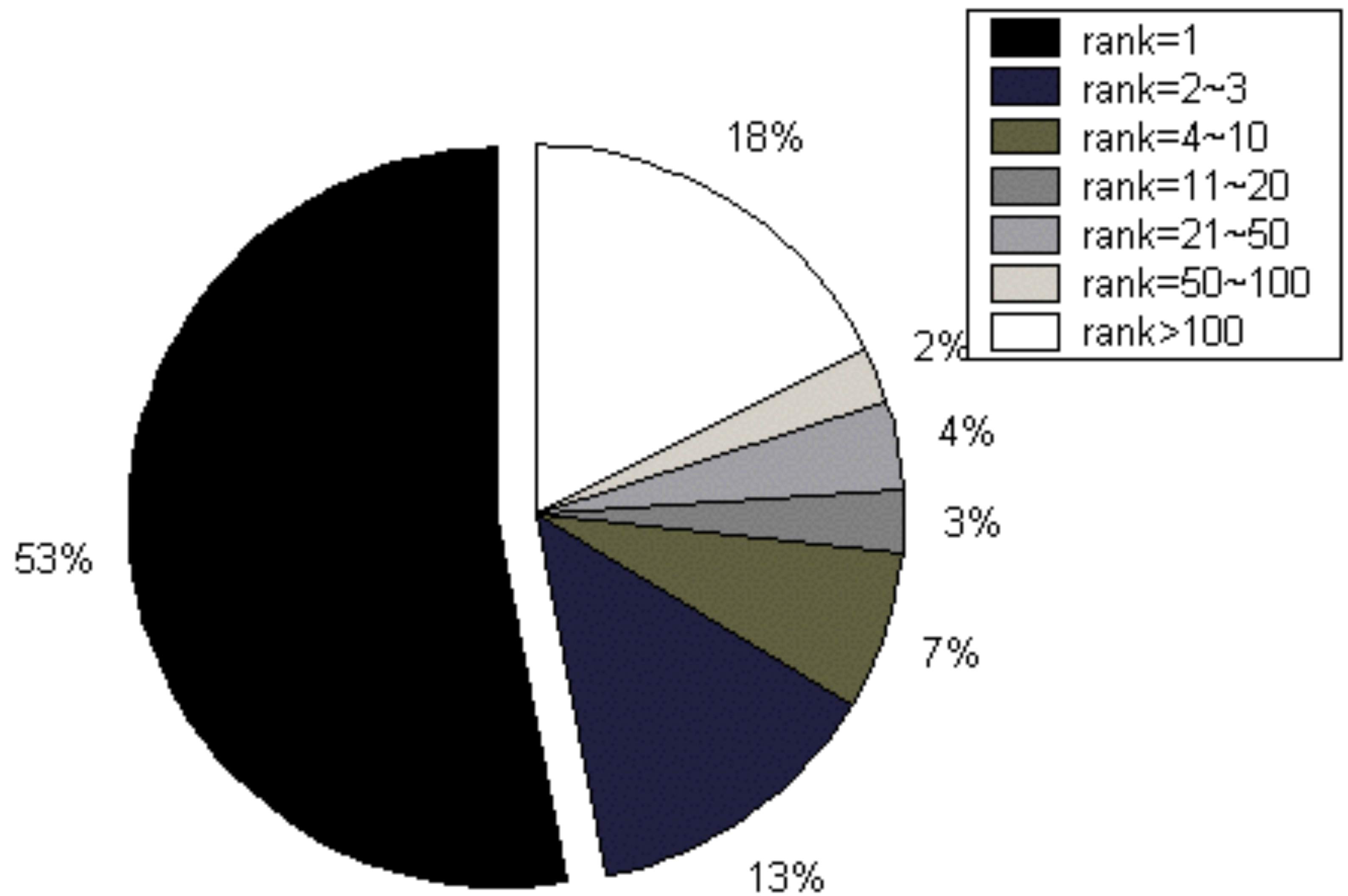


實驗結果

- 實驗環境
  - 電腦 PIII 800，256MB RAM，Windows 2000
  - 資料庫
    - 8552首，包括中文、台語、英文和日文歌曲
  - 測試歌聲wav檔
    - 從頭唱 1054 首
    - 從任意處唱 1650 首
    - 每一首長 8 秒鐘

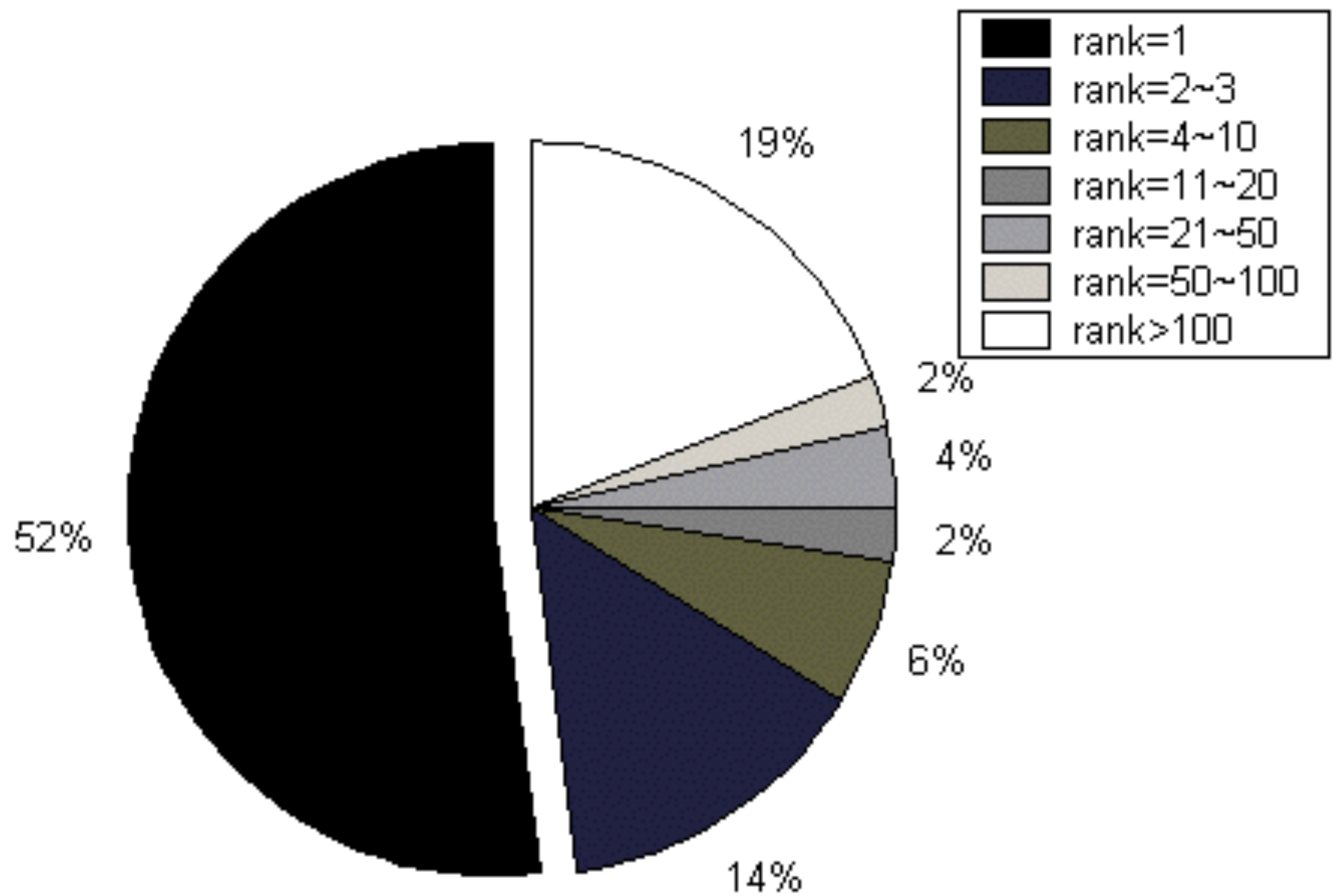
實驗結果—從頭比對

- 只用dtw
- 前三名66.41%
- 平均搜尋時間 16.71秒



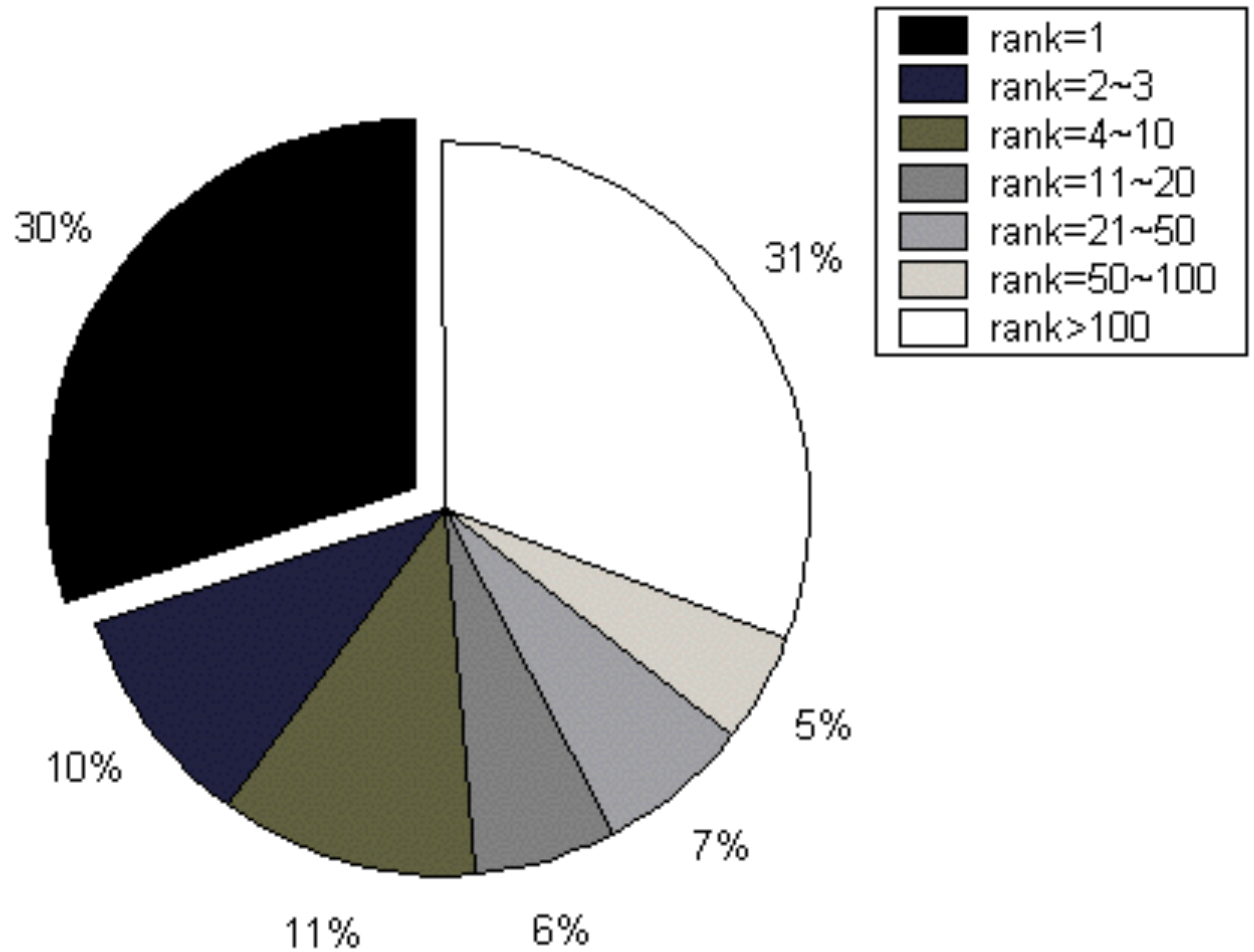
實驗結果—從頭比對

- 只用改良式dtw,
  保留100名距離
- 前三名66.13%
- 平均搜尋時間6.96
  秒



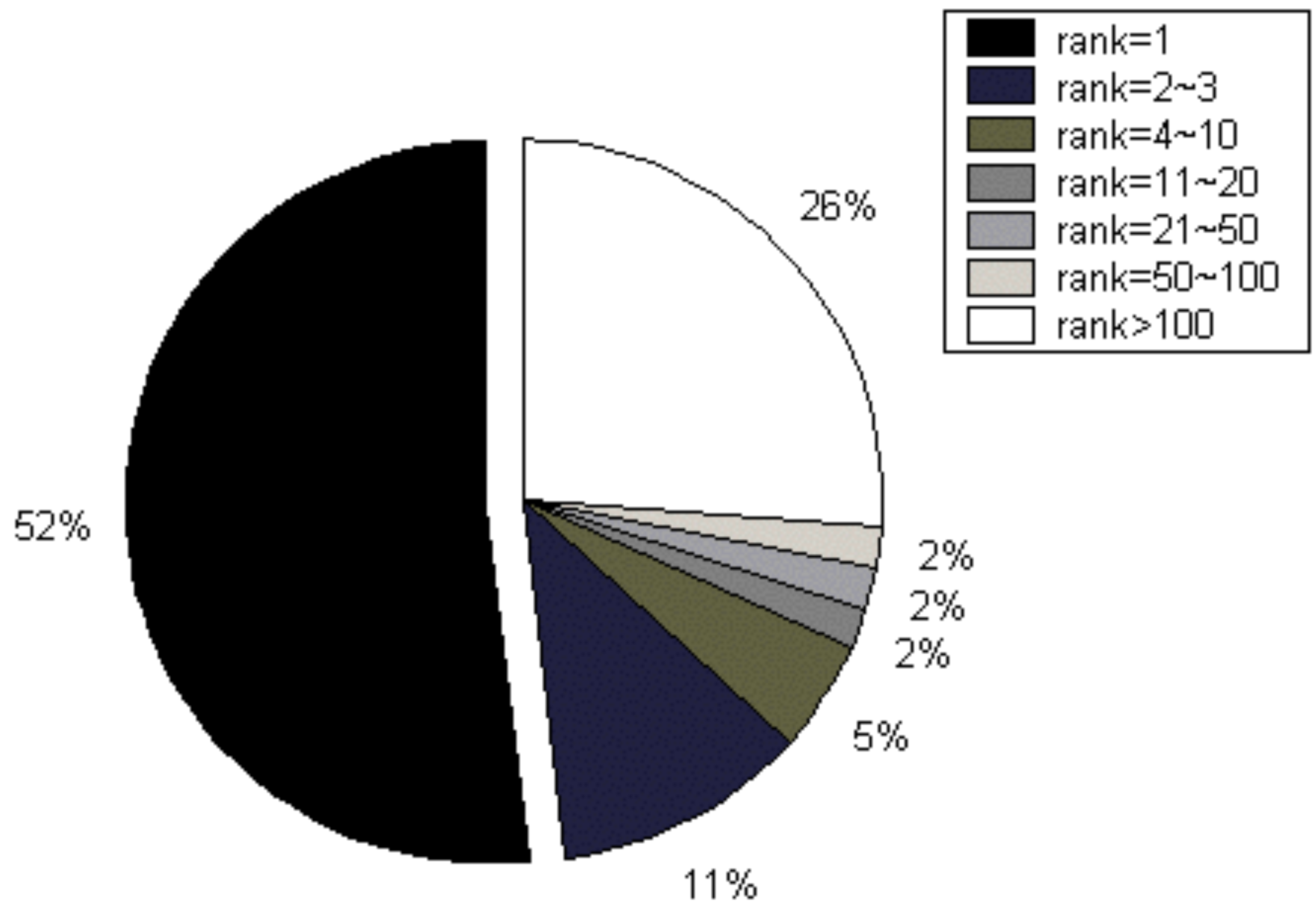
實驗結果—從頭比對

- 只用linear scaling
- 前三名39.94%
- 平均搜尋時間0.1秒

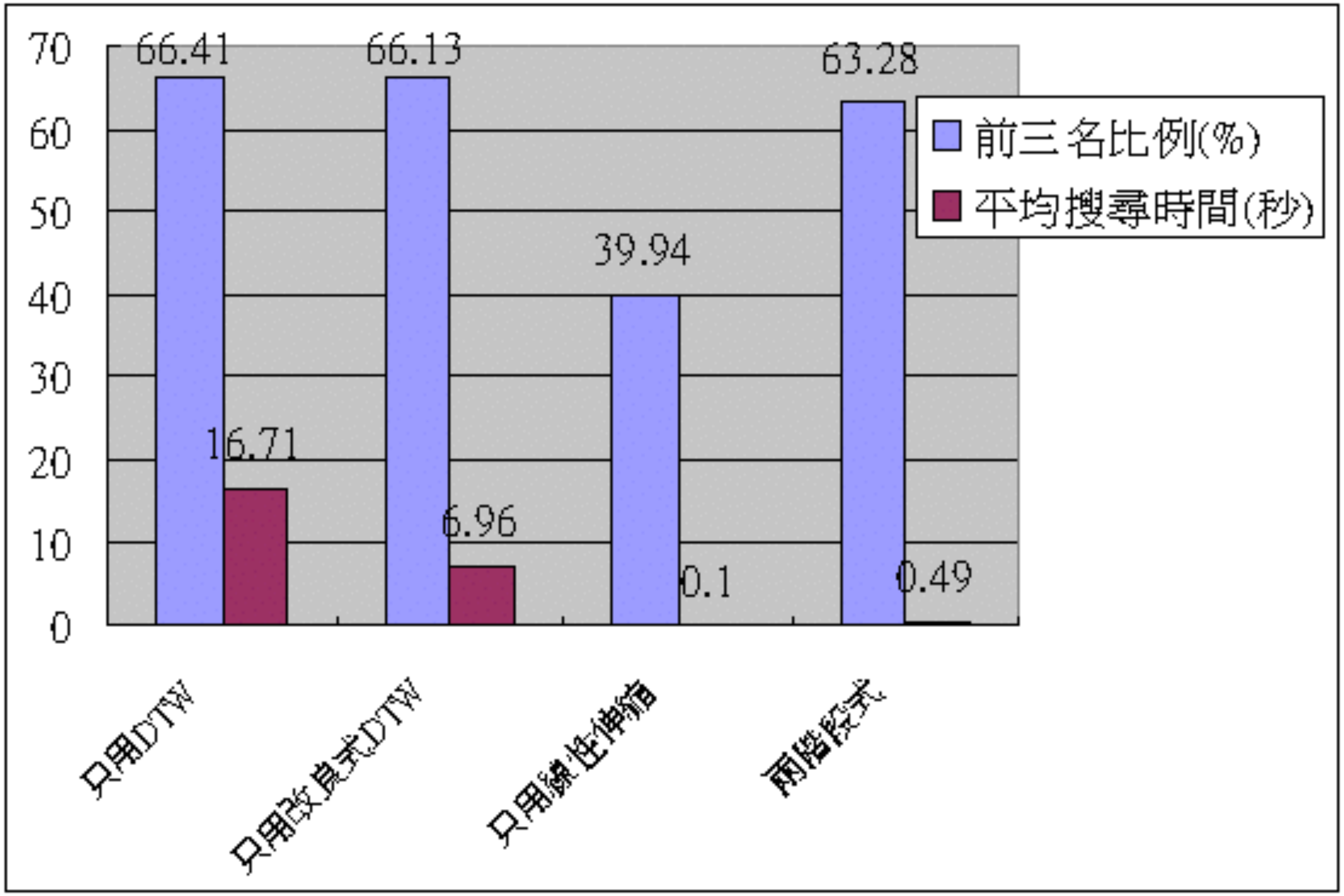


實驗結果—從頭比對

- 用兩階段式比對
- 第一階段保留200首歌進入第二階段
- 前三名63.28%
- 平均搜尋時間0.49秒

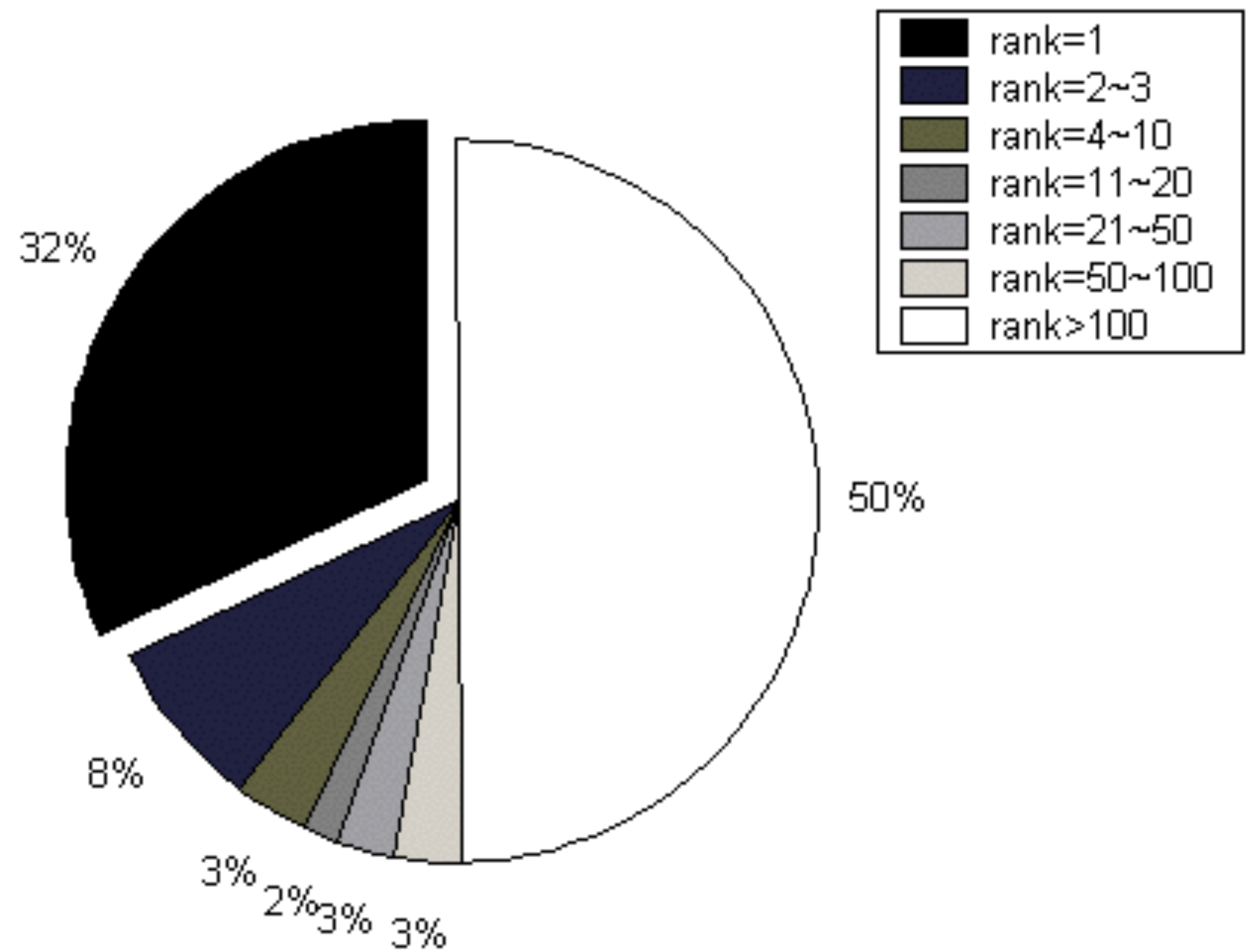


實驗結果—從頭比對比較圖

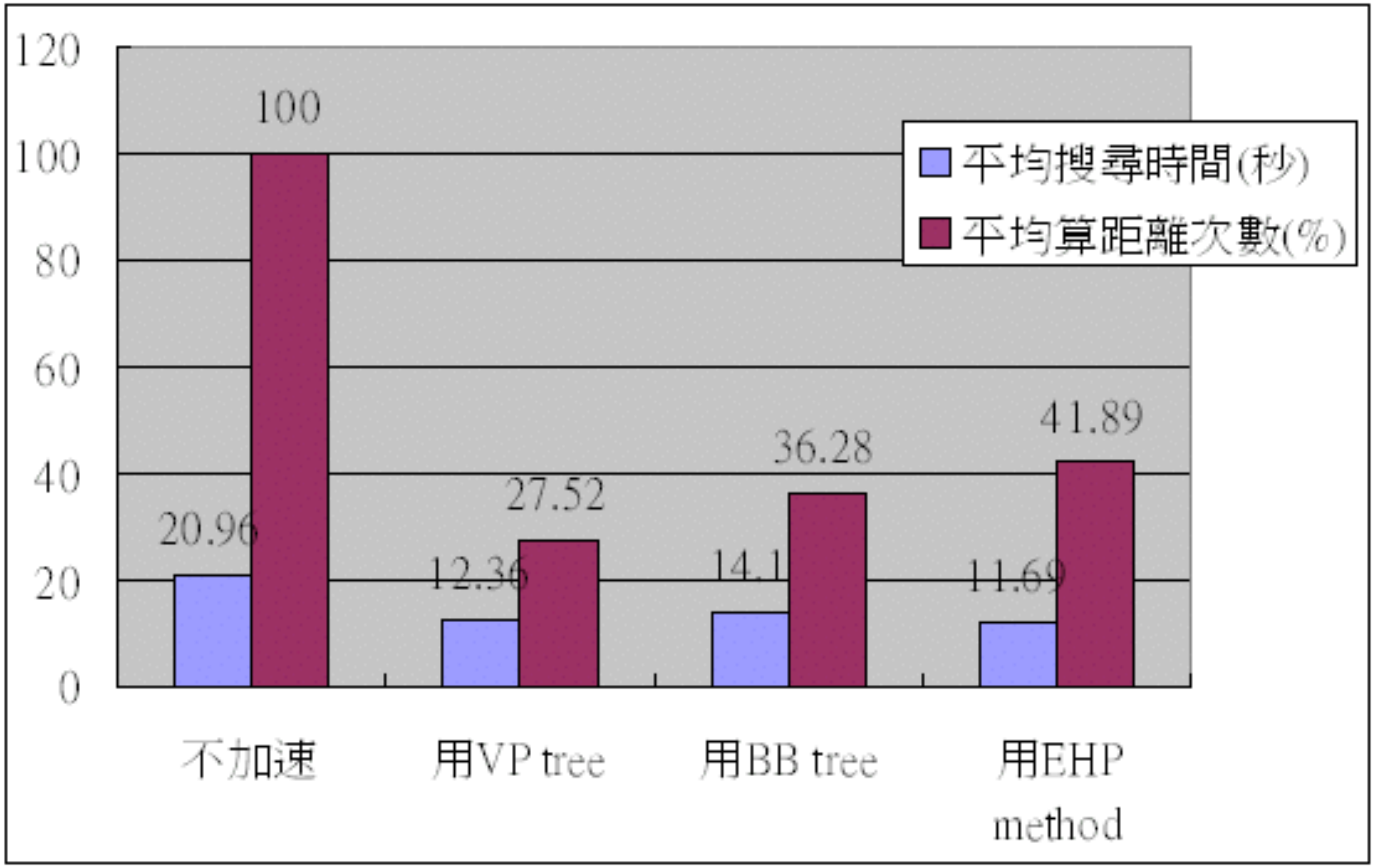


實驗結果—全曲比對

- 用兩階段式比對
- 前三名39.63%



實驗結果—全曲比對比較圖



錯誤分析

- 資料庫錯誤
  - 有前奏
  - 同一時間不只一個音符
  - 主旋律錯誤
  - 相同歌曲但不同歌名
- 測試歌聲不良
  - 有雜音
  - 氣不足、音不準
  - 唱錯
  - 拍子不準

結論

- 從頭比對
  - 只用dtw → linear scaling + 改良式dtw
    - 大約快 34 倍
    - 前三名比例下降不到 4%
- 全曲比對
  - 只用改良式dtw → linear scaling + 改良式dtw
    - 大約快 23 倍
  - 第一階段不用加速方法 → 第一階段用equal-average hyperplane partitioning method
    - 大約快 1.8 倍
    - 平均一首歌約多佔 2.7 K byte 的記憶體