Index-Based Similarity Searching with Partial Sequence Comparison for Query-by-Content Audio Retrieval

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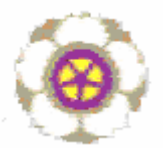
Outline

- Background and motivation
- Review of ANN based on LSH
- Proposed approach
- Experiments and results
- Conclusions and future work



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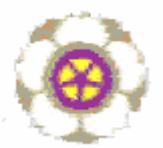
Audio Retrieval

- Explosion -- audio materials appear on Internet/personal devices
- Access -- music download/upload conveniently
- Search -- retrieval mode is often limited to the text tags
- Necessity -- query-by-content retrieval capabilities is exploited



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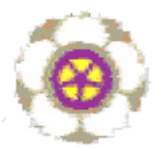
Query-by-Content Audio Retrieval

- Based on spectral similarity retrieval mode is difficult
  - High dimensionality of features
  - Complex computation
  - Large database size
- Scalable searchability need to be exploited
  - The features in service of scalable matching
  - Audio indexing structures



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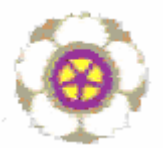
Motivation

- Depend on appropriate metrics and algorithms to reduce pairwise comparisons
- The main challenges:
  - Characterize acoustic objects with relevant spectral features.
  - Represent audio features so that they can be indexed.
  - Locate the desired music segments with a given query within the acceptable time.



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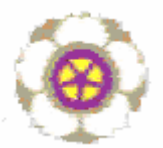

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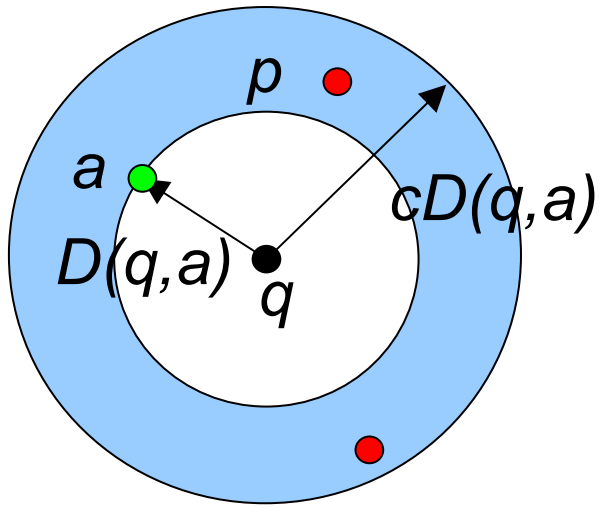
Approximate Nearest Neighbor(ANN)

- Given -- a set *P* of *n* points in R^d (*d* - dimension) and a slackness parameter **ε**>0
- Goal -- with a query point *q* whose nearest neighbor in *P* is *a*, find one/all points *p* in *P*, satisfying

  $D(p,q) <= c\, D(q,a),\ c=1+\varepsilon$
- Points in the shadowed ring are desired.



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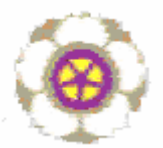
Locality-Sensitive Hashing(LSH)

- Purpose -- divide the point set *P* into subsets
- Assigns a hash value to each subset
  - All points falling into the same subset have the same hash value
- Locality sensitivity
  - The points with a short distance fall into the same subset with a high probability
  - The points with a big distance fall into the same subset with a low probability



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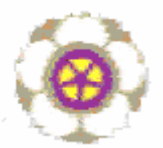

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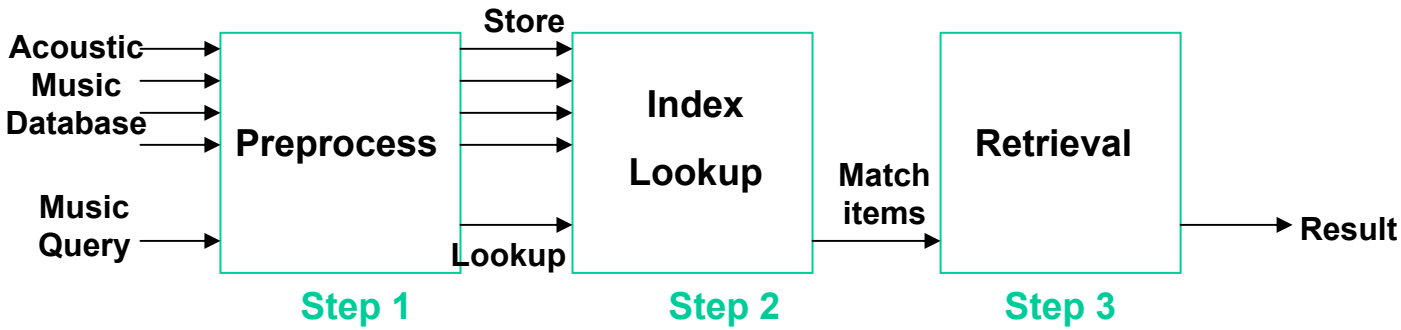
Problem Definition



- Step1-- organize database
- Step2 -- lookup the hash table
- Step3 -- compare feature sequences

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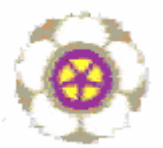
Main Idea

- Match acoustic sequences without comparing a query to each object from the database.
  - a corpus of n musical reference pieces are represented by frames $R=\{r_{i,j} : r_{i,j} \in R_i, 1 \le i \le n, 1 \le j \le |R_i|\}$
    - $r_{i,j}$ -- the j^{th} spectral feature of the i^{th} reference pieces in a high-dimension space
  - A query sequence $q_1, q_2, \ldots, q_Q$ match some resemblances by LSH-based ANN.
  - The resemble features are reorganized and compared with PSC.



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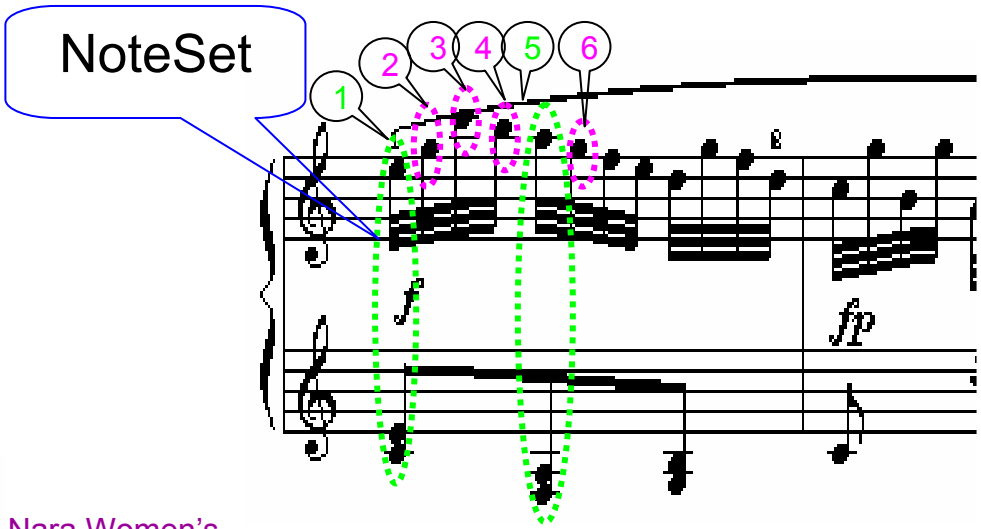
Music Score

- Music has strong descriptive composition
  - Music score implies the music theme.
  - Music score is composed of notes.
- For the simplicity of description
  - Define NoteSet as simultaneously initiated notes.



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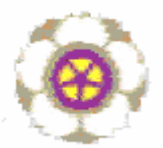
Spectral Analysis I

- Adjacent frames can be merged.
- No matter what a NoteSet plays
  - its sound lasts from tens to hundreds of milliseconds
  - it has relatively stable spectral structure
  - spectrum of the adjacent frames are correlated
- A transition
  - happens between adjacent NoteSets
  - is very short



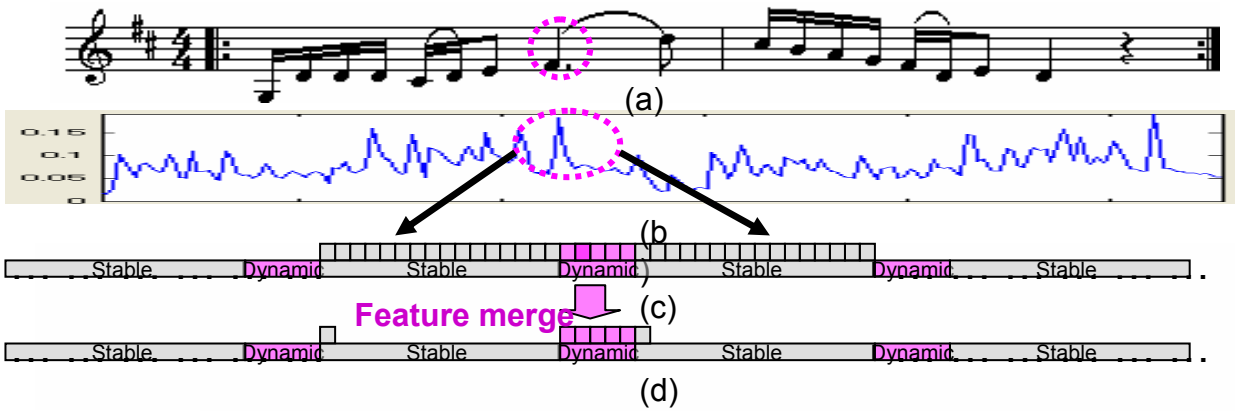
Spectral Analysis II

Example

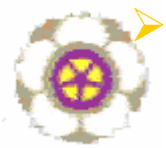
score

↓

spectrum



- (a) is the score of Alamuhan (Chinese folk).
- (b) is the corresponding energy profile.
- (c) shows the frames for feature analysis. Within a NoteSet
  - the music has a long stable state & a fixed spectral structure
  - adjacent frames tend to have the same spectral structure
- (c)→(d) is to merge the features
  - the redundant frames are removed
  - ideal case, only one frame is necessary to represent a NoteSet



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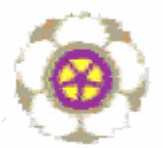
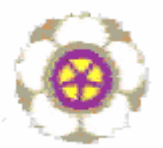
Feature Selection

- Usually Pitch is extracted as the feature
- Here MFCC is adopted as feature because:
  - STFT can stand for spectrum and is associated with music score.
  - STFT can be grouped into spectrum bins according to Mel-frequency scaling filter bank.
  - Spectrum bins can be regarded as rough spectral structure.
  - MFCC is calculated from spectrum bins. So it can represent spectrum structure.



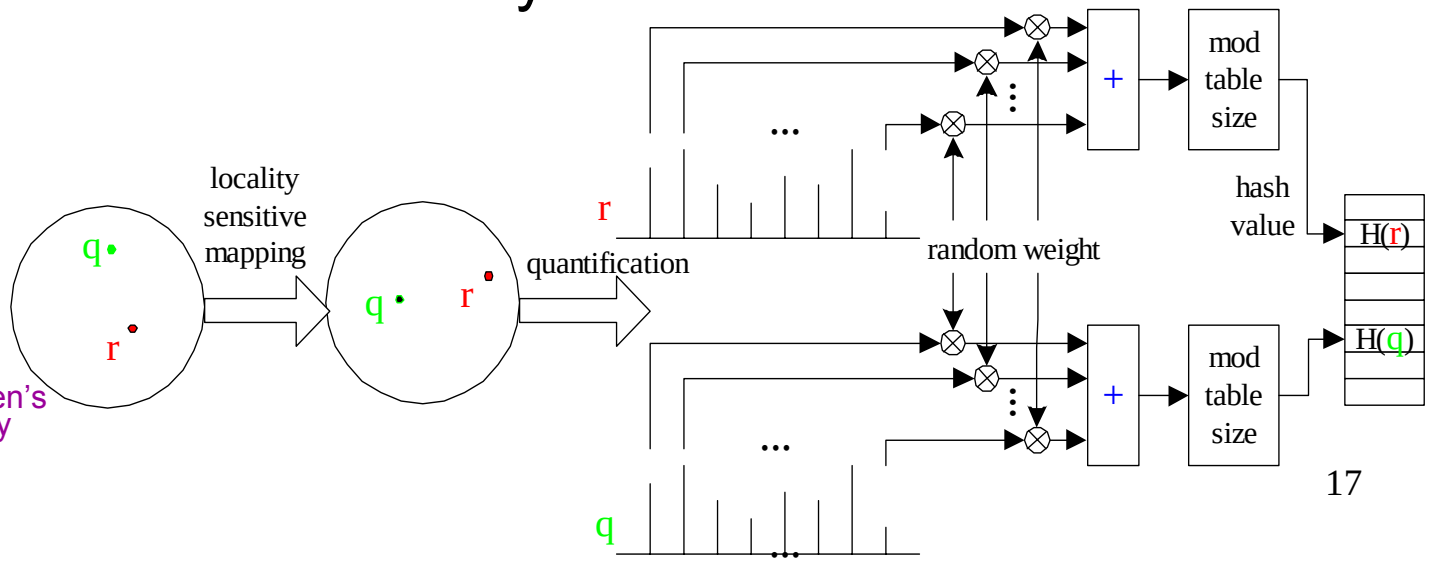
Feature Organization in Database

- Aim -- facilitate the access to the database and minimize the search time.
- The basic procedures:
  - Audio sequences are divided into small frames
  - MFCC is calculated and regarded as the feature
  - The feature is quantified and its hash value is calculated.
  - The feature is stored in the bucket according to the hash value.



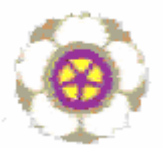
Single Hash Instance

- Hash calculation
  - Per-dimensional quantification of the feature
  - Two features with a short distance are quantified to the same integer sequences with a high probability
    - generate the same hash value
    - fall into the same bucket
  - The random weight makes the features of reference melodies almost evenly distributed.



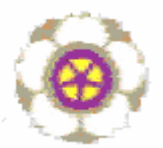
Parallel Hash Instances

- The increase of hash instances improves hit rate.
- Each hash instance contains all the features.
- Two similar frames collide in at least one of the hash instances.
- Locality sensitive mapping generate different features in each hash instance.
- Different Locality sensitive mapping functions amplify the difference.



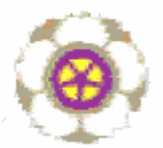
Query Stage I

- Feature Extraction
  - Divide the query into overlapped frames
  - Calculate the spectral correlation between adjacent frames
  - Merge the adjacent similar frames
  - Calculate MFCC for the remaining frames



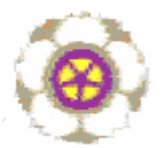
Query Stage II

- Indexing and Post Filtering
  - LSH only enables single feature indexing
  - Melody retrieval is to find the target with a sequence of features
  - With each feature of the query
    - Calculates its hash value in each hash instance
    - The features indexed by the hash values are obtained.
    - The unsimilar frames are removed so as to reduce the post computation.
    - The remaining frames from all hash tables are reorganized.



Query Stage III

- Our scheme -- Partial Sequence Comparison
  - Directly utilize the distance calculated in the filtering stage to a DTW table.
- Why partial sequence comparison ?
  - The conventional Dynamic Programming is not efficient since most of matching pairs are missing.
  - The remaining matching pairs are sparsely distributed over the Dynamic Time Warping (DTW) table.



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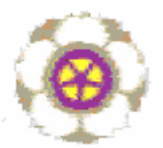

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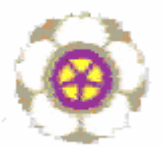
Experiment Setup

- All polyphonic melodies played by a popular Chinese 12-girl-band
  - Database size:111 melodies
  - Reference pieces: 60s
  - Query pieces: 8s
  - Sampling rate: 22.05KHz
  - Frame length: 1024
  - Frame overlap: 50%
  - STFT resolution: 11Hz (22050/2048)
- Experiments goal :
  - evaluate LSH-DP and LSH-PSC
- Evaluation metric:
  - Computation time
  - Retrieval ratio



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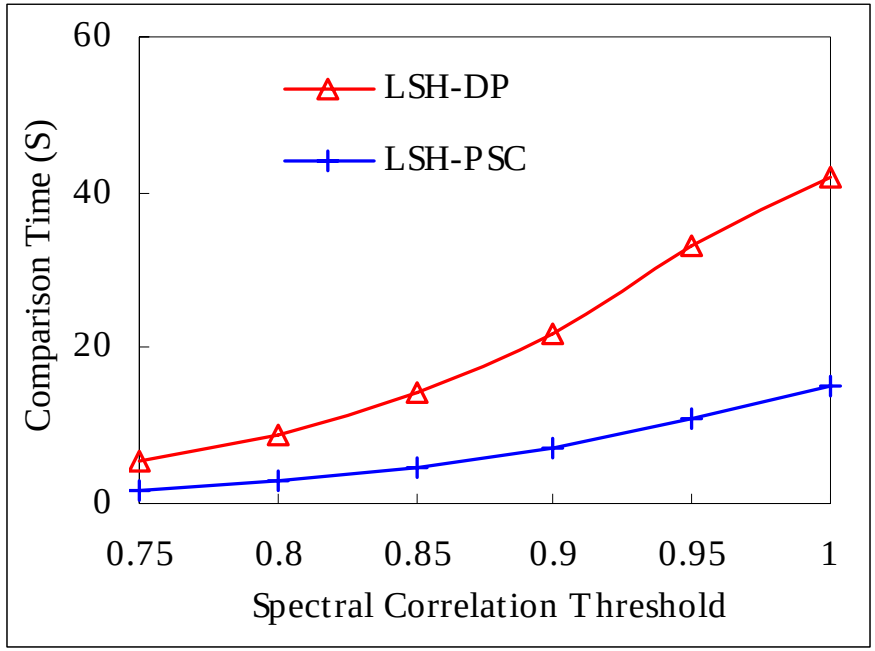
Sequence Comparison Time

- Under different Spectral Correlation threshold
  - Consider time computation from three aspects:
    - Building the hash table (ahead of the actual retrieval).
    - Filtering the features with LSH
    - Comparing feature sequences
  - Frame merge
    - Reduce both filtering time and sequence comparison time
  - PSC outperforms DP

Fig.1 Sequence comparison time in DP and PSC under different SC threshold ρ. ρ=1.0 means no frame merge. (3 hash tables, LSH filtering threshold δ=0.5)



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Sequence Comparison Time

- Under different LSH filtering threshold
  - Consider computation time from three aspects:
    - Building the hash table (ahead of the actual retrieval).
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    - Comparing feature sequences
  - Filtering in LSH
    - Reduce sequence comparison time
  - PSC outperforms DP

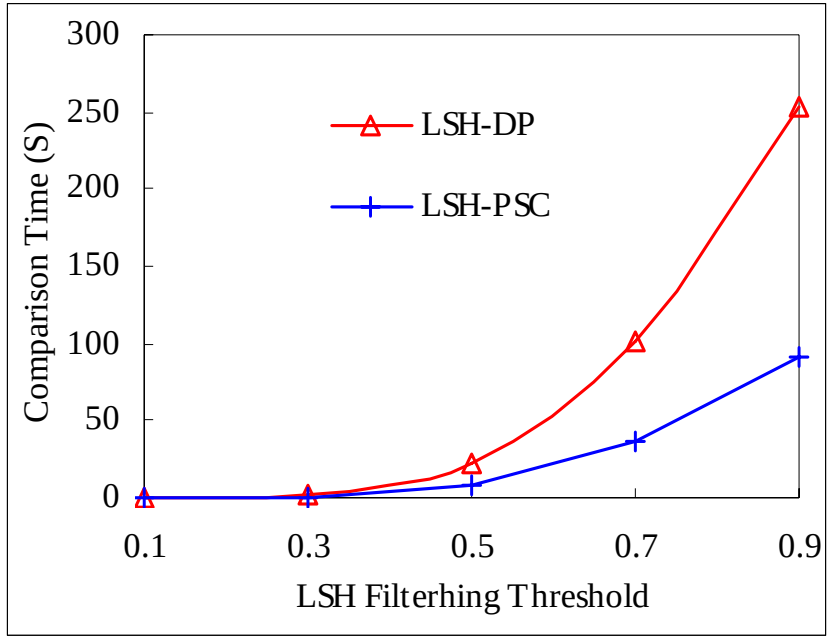
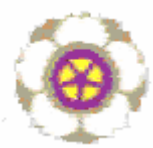


Fig.2 Sequence comparison time in DP and PSC under different filtering threshold δ (3 hash tables, SC threshold=0.9)



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Total Retrieval Time

- Computation is involved in three aspects:
  - Building the hash table (ahead of the actual retrieval).
  - Filtering the features with LSH
  - Comparing feature sequences
- Total retrieval time involves filtering and comparison time
  - Most of the time is spent in filtering stage
- Effectiveness of LSH-PSC
  - LSH effectively reduces the number of pairwise comparison
  - PSC further reduces the sequence sequence comparison

Table 1. The total retrieval time consumed for 111 queries under different schemes. For LSH, the filtering time is about 65.4s at at ρ=0.9 and about 100s atρ=1.0. (3 hash instances, LSH filtering threshold δ=0.5)

Scheme	LSH-DP (ρ=0.9)	LSH-DP (ρ =1.0)	LSH-PSC (ρ =0.9)	LSH-PSC (ρ = 1.0)	DP (ρ = 1.0)
Time(s)	87.6	139.2	72.8	118.7	1519.7

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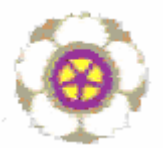
Retrieval Ratio

- Under different Spectral Correlation threshold
  - Frame merge reduces the retrieval time at the cost of retrieval ratio
    - A small SC threshold results in less computation time
    - While the retrieval ratio is also affected.
  - The effect is little when the SC threshold is bigger enough

Table 2. Top-4 retrieval ratio under different SC threshold ρ (3 hash tables, δ =0.5).

ρ	0.75	0.8	0.85	0.9	0.95	1.0
LSH-DP	0.928	0.955	0.982	0.982	0.991	0.991
LSH-PSC	0.856	0.892	0.937	0.946	0.964	0.982



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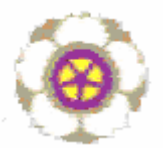
Retrieval Ratio

- Under different filtering threshold
  - LSH filtering removes the unsimilar features
    - A small filtering threshold reduces the sequence comparison time.
    - At the cost of reduced retrieval ratio.
  - The effect is little when the filtering is bigger enough

Table 3 Top-4 retrieval ratio under different filtering threshold (3 hash tables, ρ=0.9)

δ	0.1	0.3	0.5	0.7	0.9
LSH-DP	0.5945	0.973	0.982	1.0	1.0
LSH-PSC	0.604	0.914	0.946	0.977	0.98



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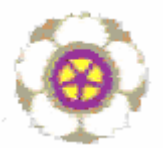

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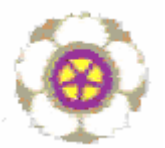
Conclusions and Future Work

- Our contribution
  - Index-based query-by-content audio retrieval
    - Efficient organization of audio features
    - Partial sequence comparison
  - Effectiveness of proposed algorithms
    - Computation time
    - Retrieval ratio
- Future work
  - Evaluation of scalability of the proposed scheme with a larger database
  - Application of query-by-content audio retrieval in ubiquitous environment.



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