Piecewise Linear Representation of Feature Trajectories by Dynamic Segmentation

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Background

Objectives
- Quick search of audio/video signals

Applications
- Retrieving broadcast music and movies
- Checking copyright materials

Problems
- High dimensionality of features
  - Matching calculation: huge
  - Indexing algorithm: unsuitable
- Feature dimension reduction required

Related Work
- KLT or SVD over all feature spaces = poor performance
- Kegl et al. [PAMI2000]: principal curves = huge cost
- Aggarwal et al. [SIGMOD99]: project clustering = huge cost
- Keogh et al. [KAIS2001, SIGMOD2001]: locally adaptive partitioning = feasible for wave-form signals
Approach

Piecewise linear representation of feature trajectories

Obtaining representation

- **Dynamic segmentation** [ICASSP2003 (ICME2003)]: partitioning feature trajectories dynamically to minimize average dimensionality
- **Segment-based PCA** [ICASSP2002]: perform Principal Component Analysis (PCA) in every segment

**Dynamic Segmentation**

**Algorithm**
- Determine the segment boundaries, given a shiftable boundary range, to minimize the average dimensionality per frame
- Optimal solution obtained by Dynamic Programming (DP)

\[
T^* = \left\{ t_j \right\}_{j=0}^M = \arg \min_{t_j \in T_j \forall j} \frac{1}{M} \sum_{i=1}^{M} (t_j - t_{j-1}) c(t_{j-1}, t_j, \sigma)
\]

\[
\text{Average dimensionality per frame}
\]

\[
\Delta^+ \leq \Delta^0 \leq \Delta^-
\]

**Problem**
- Requires huge calculation (cost \( = O(M\Delta^2) \))

**Note:** \( M = \) number of segments, \( \Delta = \) width of shiftable range
Calculation Cost Reduction

**Local Search**
- Determine each boundary independently and in order of time

\[ t_j^* = \arg \min_{t_j \in T_j} \frac{(t_j - t_{j-1}^*)c(t_{j-1}, t_j, \sigma) + (t_{j+1}^0 - t_j) c(t_j, t_{j+1}^0, \sigma)}{t_{j+1}^0 - t_{j-1}^*} \]

- **Calculation cost** = \( O(M\Delta) \)

**Coarse-to-Fine Search**
- Coarse stage:
  Search roughly in shiftable range
- Fine stage:
  Search only in the portion where the dimensionality change occurs
- Theoretically determine the minimum number of calculations
  - Determine the minimum number of calculations in the coarse stage
    \[ \hat{x} = \arg \min_x f(x) = \arg \min_x 2\left\{2x + 3 + K\Delta(x + 1)^{-1}\right\} \]
  - **Calculation cost** = \( O(M\sqrt{K\Delta}) \) \( \text{ ( } K : \text{ constant s.t. } K << \Delta \text{ )} \)
Experiments

Conditions
- Database: video recording of 24-hour TV broadcast
- Feature dimensionality = 256
- Number of segments = 1000
- Required contribution ratio = 0.95
- Shiftable range width = 500
- Initial boundary positions: obtained by equi-partitioning

Results: Summary
- Dimension reduction performance
  - Reduce dimensionality by partitioning feature sequences
    - 1/30 of non-partitioning value
  - Reduce dimensionality further by dynamic segmentation
    - 87.5% of equi-partitioning value
    - Performance almost identical to DP (optimal) or local search
- Computational cost
  - 1/5000 of DP, 1/10 of local search
Experiments

Results: Detailed

- Dimension reduction performance
  (Top left: equi-partitioning, Top right: dynamic segmentation)

- Computational cost of dynamic segmentation
  (Bottom right)