



Adaptive Cluster Distance Bounding for Similarity Search in Image Databases

Sharadh Ramaswamy and Kenneth Rose Signal Compression Lab {rsharadh,rose}@ece.ucsb.edu

Introduction

- Huge image databases are central in many apps. e.g. bio-imaging
- Images rep. by high-dim. features
- Content-based retrieval is inevitable
- Fast similarity search needed for quick navigation



http://www.cs.cmu.edu/~juny/Prof/images/CBIR.jpg

Image Features and Distances

Popular image features

- color histogram
- texture descriptors
- shape descriptors
- Common similarity measure Euclidean distance (not perceptually optimal)
- Mahalanobis distances (thru' relevance feedback) possible

Storage on Hard-disks

- High-dim. features stored on a hard-drive
- Access thru' blocks/pages (fixed size)
- Sequential/serial or random access
- Random IOs more expensive per page
- Every access = 1 random
 IO + rest serial IOs



Multi-dimensional Indexes

- Tree-like indexes efficient in low dimensions e.g. R-tree
- 'Curse of dimensionality' hinders R-trees etc., creates large no. of random IOs
- Scan-like methods more effective at high dimensions
- Vector Approximation (VA)-File popular

VA-File based Indexing

- Quantize each dimension uniformly
- Quantize each element of data-set



VA-File based Indexing

- Quantize each dimension uniformly
- Quantize each element of data-set
- Create approximation file
 - store quantization bit-strings for each element



VA-File –Query processing

- 1. Read approximation file
- 2. Establish lower and upper distance bounds to occupied cells
- 3. Eliminate irrelevant cells
- Access all survivors in order of lower bounds
- If kth lowest distance found so far, less than next lower bound, STOP (kNNs found) Else read next survivor.



VQ/Clustering for Indexing

- VQ is optimal in compression
 smaller preprocessing storage
- Similar feature vectors stored together
 each cluster has several candidate vectors
 better use of page access structure
- Extensively used in approx NN search
- Cluster-distance bounding for exact NN
 bounds using MBRs and MBSs are loose

Bounding Query-Cluster Distance



Cluster Distance Bounding



Adaptive Cluster Distance Bounding



- Bound distance with multiple hyperplanes
 - use tightest distance bound
- Cluster boundaries are linear
 - use them as (separating) hyperplanes
 - no need to store hyperplanes

Proposed Indexing Scheme

1. Cluster data-set through VQ/K-means

- "nearest neighbor" partitioning for linear boundaries
 evaluate "offline" and store cluster supports
- 2. Bound query-cluster distance with hyperplane bound
- 3. Retrieve clusters in order of distance
 - IF kNN distance so far < distance to next cluster STOP (kNNs found)
 ELSE read next cluster (till all clusters read)

Experiments & Results

- Data-sets AERIAL (60 dim, 275K)
 - BIO-RETINA (62 dim, 208K)
- Clustering with GLA/K-means
- No. of clusters varied (20 600)
- VA-File Quantization varied (3-8 bits/dim)
- Page size 8kB
- 2D Performance Metric –

(Random IOs ,Serial IOs)

IO Performance - AERIAL





IO Performance – BIO-RETINA





Pre-processing Storage (BIO-RETINA)



Lower pre-proc. Storage!!

Computational Costs – BIO-RETINA



Results & Future Work

- Real data-sets exhibit significant dependencies across dimensions
- VQ/Clustering exploits correlations
- Proposed hyperplane bound is tight and provides for efficient spatial filtering
- Huge gains in IO complexity possible over VA-File and MBS bounds
- To be extended towards Mahalanobis distances and relevance feedback...