Kernel Indexing for Relevance Feedback Image Retrieval

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OVERVIEW

• Motivation—Flexible metric/indexing dilemma
• Why kernel indexing
• Kernel distances: AQK and 1SVM
• Kernel indexing
  • Kernel M-trees
  • Kernel VA-files
• Experiments
• Summary

Relevance Feedback

Accuracy
■ Capture user's perceived similarity

Efficiency
■ Reduce nearest neighbor computation
Flexible Distance/Indexing Conflict

- Indexing requires off-line selection of distances.
- Optimal retrieval demands on-line distance adaptation through relevance feedback.
- When the distance is modified the index structure is no longer optimal and may not be even valid.

Resolving Flexible metric/Indexing Conflict

- Few systems have been developed to address flexible metric/indexing dilemma: VA-Files. (Webber et al. VLDB’98; Wu & Manjunath, ACM Multimedia’00)
- VA-Files cannot support relevance feedback retrieval using kernel distances.
- Develop kernel indexing to potentially resolve this conflict.
Kernel Distances

• AQK:
  
  (Heisterkamp, Peng & Dai, CVPR'01)

• 1SVM:

  (Tax & Duin, ESANN'99; Chen et al., ICIP'01)

1SVM Kernel Distance

Moving center in induced space is captured by dynamic coefficients in input space.
Kernel Indexing

- It is **dynamic** and **highly non-linear** in input space but remains **Euclidean** in induced space
- Build index structure in induced space to support relevance feedback retrieval
  - M-trees or VP-Trees
  - VA-Files

Kernel M-Trees

- Why metric space based index methods?
- Distance between any two objects in induced space can be computed:
- M-trees or Vantage-Point (VP) trees can be built in induced space.
- In particular, M-tree code is publically available.

Vector Approximation (VA) Files

- Phase I—linear scan of approximation file or bins
Vector Approximation (VA) Files

Kernel VA-Files

- Phase II—linear scan of data from candidate bins

| \( \phi(\mathbf{x}) \) | KVA-File | \( \alpha_0 \ | \ \phi_0(\mathbf{x}) \) |
|-----------------|----------|-----------------|
| 1               | 0.1      | 0.29             |
| 2               | 0.15     | 0.17             |
| 3               | 0.32     | 0.0029           |
| 4               | 1.1      | 0.0017           |
| 5               | 1.2      | 0.0             |
| 6               | 1.2      | 0.030            |
| Query           | 0.3      | 0.65             |
|                 | 0.03     |                 |

Bounds for AQK and 1SVM can be established in a similar manner.
Kernel VA-Files

- VA-Files can be built from basis vectors and distance bounds in induced space.
- KVA-Files provide two levels of compression:
  - Number of basis dimensions
  - Number of bits per dimension

basis dimensions
- better I/O access
- approximation file

bits p. dimension
- poor I/O access
- approximation file

Experiments

- Hemera Photo-Object image data: 100,000 images
  - Very Heterogeneous
- Simple color histogram to represent images
- 200 random samples as query images
  - Kernel M-trees
  - Kernel VA-Files

Experiments with Kernel M-Trees

- 20 nearest images provide relevance feedback

66 feature dimensions

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<th>KernelIndex</th>
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198 feature dimensions

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Experiments with Kernel M-Trees

Input or feature indexing?

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Average distance calculations per query

Experiments with Kernel VA-Files

- 462 dimensional color histogram features.
- Block size: 22180 bytes (12 records per block).

- 100 basis vectors with varying bits per dimension.
- Decreasing # of bits per dimension increases data blocks visited but also decreases the approximation file.

- 75 basis vectors with 8 bits per dimension.
- Approximation file was 4% of original data file.
Summary

• Kernel indexing techniques are introduced that support relevance feedback retrieval using kernel distances.
• Efficacy of kernel indexing is validated using a large image database.