Compact Kernel Hashing with Multiple Features

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Background and Related Work

Background

- The explosive growth of the vision data motivates the recent studies on hashing based nearest neighbor search (ANN)
- Locality-Sensitive Hashing (LSH) gives the paradigm of hashing based ANN
- Various scenarios: unsupervised, supervised, kernelized, and multiple probes

Related Work

- Adapтивly combining diverse complementary features can give improved performance
- Existing multiple feature hashing approaches either simply post-combine linear outputs of each feature type or equally pre-concateenate all features as one

Main Issues

- The correlation and importance of each feature type are still not fully exploited
- Computationally expensive in both training and searching

Multiple Feature Kernel Hashing

Notations

- a set of N training examples with M visual features
- \( X_n^{(m)} \in \mathbb{R}^{d_m \times 1} \): the m-th feature (d_m dimension) of n-th sample
- \( X^{(m)} = [X_1^{(m)}, X_2^{(m)}, ..., X_n^{(m)}] \): the m-th feature of all data

Key Idea

- Learn a kernel space incorporating multiple features, where the neighbor relationships can be well preserved.

Nonlinear feature mapping

- a series of embedding functions \( \phi_{n}(\cdot) \) corresponding to each visual feature
- nonlinear mapping of i-th sample \( \phi_i(x) = [\phi_1^T(x_i), ..., \phi_p^T(x_i)]^T \)
- linear projection hashing \( h_p(x_i) \equiv \text{sign}(V_p^T \phi(x_i) + b_p) \)

Multiple kernel form

- \( V_p \) in kernel space can be represented as a combination of R landmarks \( Z_r \)
- let \( K^{(m)} \) denote the kernel corresponding to \( \phi_{m}(\cdot) \), then \( \phi(\cdot) \)
  defines a kernel \( K = \sum_{m=1}^{M} \mu_m K^{(m)} \)
- kernel hashing
  \( h_p(x_i) \equiv \text{sign}(W_p K_i + b_p), p = 1, ..., P \)

Optimization

- Objective function similar to that of spectral hashing

\[ \mathcal{L}(S, W, h_p) = \frac{1}{2} \sum_{i,j} S_{ij} ||Y_i - Y_j||^2 + \lambda ||W||^2 \]

Spectral embedding loss regularization

- Alternating optimization
- Update hashing parameters: \( (W, h) \)
- Update linear combination coefficients: \( \mu \)

Datasets

- CIFAR-10: 60K, 384D GIST + 300D SIFT BoW
- NUS-WIDE: 270K, 128D texture + 225D color

Experiments

- MAP for Hamming ranking
- Recall, precision of top results

Conclusion

- Efficient multiple feature hashing.
  - similarity preserving hashing with linearly combined multiple kernels
  - efficient alternating optimizing way