Multi-View Complementary Hash Tables for Nearest Neighbor Search

Xianglong Liu*, Lei Huang*, Cheng Deng†, Jiwen Lu†, Bo Lang*

*State Key Lab of Software Development Environment, Beihang University, Beijing, China
†Xidian University, Xi’an, China
‡Tsinghua University, Beijing, China

Background and Related Work

**Background**
- The explosive growth of the vision data motivates the recent studies on hash based nearest neighbor search (NNS)
- Locality-Sensitive Hashing (LSH) is able to achieve compressed storage and efficient computation in NNS
- Building multiple hash tables and probing multiple buckets can boost the overall NNS performance

**Related Work**
- The most widely-used strategy: random LSH-based multi-table, working like multi-index hashing [27]
- Complementary hash tables: a sequential learning method [37]
- A general multi-table construction strategy: bit selection over existing hashing algorithms [21]

**Main Issues**
- It often requires a huge number of tables without eliminating the table redundancy
- Hash tables are usually learned only from single type of data source, while adaptively combining them can help learn more informative hash functions

Complementary Multi-View Tables

**Table Complementarity**
- sequential learning: for each view the similarities on the inconsistent neighbor pairs will be amplified at next round

\[ \hat{S}_{ij}^{(m)} = S_{ij}^{(m)} \exp(-\alpha^{(m)} P_{ij}) \]

**Exemplar Reweighting**
- pursue the table complementarity and meanwhile preserve the low-rank similarity; calibrate the role of each exemplar

\[ \hat{Z}^{(m)} = \Gamma^{-1}Z^{(m)}\Pi^{(m)} \]

**Proposition 1:** Theorem 1 still holds when using the nonlinear feature map based on exemplar reweighting

\[ z^{(m)}(x) = \sum_{b=1}^{B} \frac{\hat{Z}^{(m)}(x)b}{\hat{Z}^{(m)}(x)b} \frac{1}{\sum_{b=1}^{B} \hat{Z}^{(m)}(x)b} \frac{1}{\sum_{b=1}^{B} \hat{Z}^{(m)}(x)b} \]

Experiments

**Datasets**
- CIFAR-10: 60K, 384D GIST + 300D SIFT BoW
- TRECVID: 250K, 512-D GIST + 1000-D spatial pyramid SIFT BoW
- NUS-WIDE: 270K, 128D texture + 225D color + 500-D SIFT BoW

**Results**
- Hash table lookup: recall, precision within a Hamming radius
- Hamming distance ranking: average precision of the top results

Conclusion
- The First Multi-View Complementary Multi-Table Method
  - Exemplar-based feature fusion: adaptively exploit multi-view information and guarantee the fast computation
  - Exemplar reweighting: eliminate table redundancy in a fast boosting manner