UF UNIVERSITY of FLORIDA
J. Crayton Pruitt Family Department of Biomedical Engineering

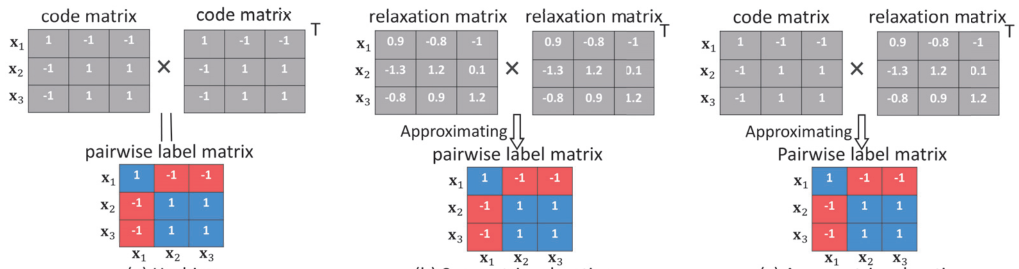
Kernel-Based Supervised Discrete Hashing for Image Retrieval

Xiaoshuang Shi, Fuyong Xing, Jinzheng Cai, Zizhao Zhang, Yuanpu Xie and Lin Yang
University of Florida

BIQI^2 BIOMEDICAL IMAGE COMPUTING AND IMAGING INFORMATICS

Abstract

In this paper, we propose a novel yet simple kernel-based supervised discrete hashing method via an asymmetric relaxation strategy. Specifically, we present an optimization model with preserving the hashing function and the relaxed linear function simultaneously to reduce the accumulated quantization error between hashing and linear functions. Furthermore, we improve the hashing model by relaxing the hashing function into a general binary code matrix and introducing an additional regularization term. Then we solve these two optimization models via an alternative strategy, which can effectively and stably preserve the similarity of neighbors in a low-dimensional Hamming space. The proposed hashing method can produce informative short binary codes that require less storage volume and lower optimization time cost. Extensive experiments on multiple benchmark databases demonstrate the effectiveness of the proposed hashing method with short binary codes and its superior performance over the state of the arts.



(a) Hashing (b) Symmetric relaxation (c) Asymmetric relaxation

Motivations

- NP-hard objective function– there is no exact solution known
- Symmetric relaxation- relaxing the discrete matrices into continuous matrices can make the problem easily be solved, while it would generate accumulated quantization errors between the discrete and continuous matrices
- Discrete matrix preservation- directly learning binary codes can reduce the accumulated errors.

NP-hard objective

$$\min_{A} \|sgn(A\bar{K})^T sgn(A\bar{K}) - rS\|_F^2$$

Symmetric relaxation

$$\min_{A} \|(A\bar{K})^T (A\bar{K}) - rS\|_F^2$$

Objective

- *Kernel supervised discrete hashing with hashing function preserved (KSDH_H)*

Objective function

$$\min_{A} \|H^T A\bar{K} - rS\|_F^2$$
$$s.t. A\bar{K}\bar{K}^T A^T = nI_r, H = sgn(A\bar{K}).$$

The hashing function H is preserved in the objective function. The constraint $A\bar{K}\bar{K}^T A^T = nI_r$ is derived from the constraint $HH^T = nI_r$, which enforces r bit hashing codes mutually uncorrelated such that the redundancy among these bits is minimized.

- *Kernel supervised discrete hashing with a relaxed binary code matrix (KSDH_B)*

Objective function

$$\min_{A} \|B^T A\bar{K} - rS\|_F^2 + \lambda\|B - A\bar{K}\|_F^2$$
$$s.t. AK\bar{K}^T \bar{A}^T = nI_r$$

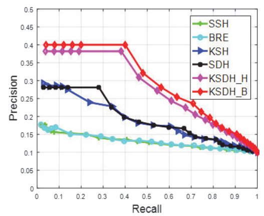
B represents the binary codes of training data, the term $\|B - A\bar{K}^T\|_F^2$ aims to reduce the accumulated errors, λ is to balance the semantic information and accumulated errors. In addition, the regularization term can guarantee the objective function to have a stable optimal solution

Experiment

- We evaluate KSDH_H and KSDH_B on four publicly available benchmark databases: CIFAR-10, MNIST, Youtube and ImageNet. We compare the proposed algorithms against SSH [1], BRE [2], KSH [3] and SDH [4]. For the CIFAR-10 database, we partition it into two parts: a training subset of 59K images and a test query set 1K images, which contains ten categories with each consisting of 100 images. We uniformly select 100 and 500 images from each category to form two training sets, respectively.

Ranking performance and training time (second) on the CIFAR-10 database

Method	n=1000				n=5000			
	MAP			Time	MAP			Time
	8-bit	16-bit	32-bit	32-bit	8-bit	16-bit	32-bit	32-bit
NN	0.1755			-	0.1713			-
SSH[1]	0.1544	0.1517	0.1684	0.02	0.1540	0.1529	0.1598	0.66
BRE[2]	0.1587	0.1715	0.1852	156.36	0.1589	0.1723	0.1905	1989.20
KSH[3]	0.2474	0.2782	0.3135	21.75	0.2787	0.3317	0.3746	692.78
SDH[4]	0.3580	0.4937	0.5314	0.05	0.5224	0.5889	0.6218	0.70
KSDH_H	0.5102	0.5109	0.4633	0.50	0.5661	0.5974	0.6131	3.10
KSDH_B	**0.5185**	**0.5408**	**0.5495**	0.05	**0.5995**	**0.6208**	**0.6317**	1.65



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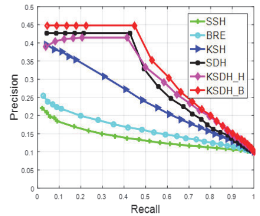

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Reference: [1] Wang, J., Kumar, S., Chang, S.F.: Semi-supervised hashing for large scale search. TPAMI 34(12) (2012) 2393–2406
[2] Kulis, B., Darrell, T.: Learning to hash with binary reconstructive embeddings (2009) NIPS.
[3] Liu, W., Wang, J., Ji, R., Jiang, Y.G., Chang, S.F.: Supervised hashing with kernels (2012) CVPR.
[4] Shen, F., Shen, C., Liu, W., Shen, H.T.: Supervised discrete hashing (2015) CVPR.