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# Supervised discrete discriminant hashing for image retrieval

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ABSTRACT

Most existing hashing methods usually focus on constructing hash function only, rather than learning discrete hash codes directly. Therefore the learned hash function in this way may result in the hash function which can-not achieve ideal discrete hash codes. To make the learned hash function for achieving ideal approximated discrete hash codes, in this paper, we proposed a novel supervised discrete discriminant hashing learning method, which can learn discrete hashing codes and hashing function simultaneously. To make the learned discrete hash codes to be optimal for classification, the learned hashing framework aims to learn a robust similarity metric so as to maximize the similarity of the same class discrete hash codes and minimize the similarity of the different class discrete hash codes simultaneously. The discriminant information of the training data can thus be incorporated into the learning framework. Meanwhile, the hash functions are constructed to fit the directly learned binary hash codes. Experimental results clearly demonstrate that the proposed method achieves leading performance compared with the state-of-the-art semi-supervised classification methods.



## 1. Introduction

In recent years, hashing technique has become an important tool to deal with variety problems of large-scale databases such as object recognition [1], image retrieval [2–4], information retrieval [5–7], Image matching [8] and related areas [9–12]. For these problem, hashing learning is usually to learn a series of hash function which maps the similar data samples into a similar binary hash code such that the structure of the original space can be preserved in the hash space. Existing hashing methods can be categorized into two main categories: data-independent and data-dependent.

Data-independent hashing methods usually generate random permutations or projections to map the data samples into a new feature space without considering the training data and then the sign function is applied to binarize the mapped feature. Locality Sensitive Hashing (LSH) [13] is a well-known representative data-independent hashing method, which constructs hash functions by simply using random linear projections. In addition, LSH has been generalized to other variants by accommodating other distance and similarity measures such as p-norm distance [14], cosine similarity [15] and kernel similarity [16,17]. In order to achieve high precision, long bit length hash codes need to be obtained for LSH and its variants, however, long bit length leads to reduce recall and a huge storage overhead.

Recently, data-dependent hashing methods have been developed to learn compact hash codes by taking full advantage of the information of the training data. In other words, data-dependent hashing methods usually learn a hash function from a training set, and then the learned hashing function is applied to learn hash codes. Existing data-dependent hashing methods can be divided into: unsupervised, semi-supervised, and supervised methods.

Unsupervised hashing methods try to design hash functions which can preserve the similarity in the original feature space from unlabeled data. Some well-known unsupervised hashing methods include spectral Hashing(SH) [18,19], spectral multimodal hashing [20], Iterative Quantization(ITQ) [21], inductive manifold hashing (IMH) [22], Anchor Graph Hashing(AGH) [23], Isotropic Hashing(IsoH) [24], Self-taught hashing [25], Discrete Graph Hashing(DGH) [26] and Collaborative multiview hashing (CMH) [27]. For unsupervised hashing, no label information can be exploited for constructing hash functions. In order to achieve high precision retrieval results, long bit length hash codes need to be obtained. This may lead to considerable storage overhead and longer query time.

Semi-supervised hashing methods try to incorporate the pairwise label information of few labeled data into the construction of hash functions. Some popular semi-supervised hashing methods

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include Semi-Supervised Hashing (SSH) [28,29], Semi-Supervised Discriminant Hashing (SSDH) [30], binary reconstructive embedding (BRE) [31] and Semi-supervised manifold-embedded hashing [32]. Semi-Supervised Hashing [28,29] preserves semantic similarity by utilizing the pairwise label information. Semi-Supervised Discriminant Hashing (SSDH) [30] is proposed based on Fisher discriminant analysis to learn hash codes by maximizing the separability between labeled data in different classes while the unlabeled data are used for regularization. Binary Reconstructive Embedding (BRE) [31] aims to design hash functions by minimizing the reconstructed error between the input distances and the reconstructed Hamming distances. Semi-supervised manifold-embedded hashing [32] is explored to simultaneously optimize feature representation and classifier learning, which will make the learned binary codes optimal for classification. For semi-supervised hashing, the existing semi-supervised hashing usually designs independent hashing functions learning criterion based on labeled and unlabeled training data. Thus, the design of objective functions based on the unlabeled training data do not take any prior information of the labeled information into account.

Supervised hashing methods try to exploit the label information of the training data in hashing function learning. Some well-known supervised hashing methods include kernel-based Supervised hashing (KSH) [33], supervised discrete hashing (SDH) [34], minimal loss hashing (MLH) [35], Supervised hashing via image representation learning [36], Supervised deep hashing [37–39], Quantization-based hashing [40] and Robust discrete code modeling for supervised hashing [41]. Kernel-Based Supervised Hashing (KSH) [33] is to design hashing function based on similar and dissimilar sample pairs. Supervised discrete hashing [34] learns the hashing function directly from discrete hash codes, where the learned hash codes are expected to be optimal for classification. Minimal Loss Hashing (MLH) [35] aims to preserve the pairs similarity of training samples in hash space. Supervised hashing via representation learning [36] automatically learns a good image representation tailored to hashing as well as a set of hash functions. Supervised deep hashing [37–39] builds a deep convolutional network to learn discriminative feature representations. Quantization-based hashing [40] proposes a general framework to incorporate the quantization-based methods into the conventional similarity-preserving hashing and aims to reduce the quantization error of any similarity-preserving hashing methods. Robust discrete code modeling for supervised hashing [41] devises an l2, p-norm-based binary code modeling approach, which can adaptively induce sample-wise sparsity and perform automatic code selection as well as noisy samples identification. Many existing supervised hashing methods [42–44] usually focus on the construction of the hashing function. However, the learning of the discrete hash codes is very important for hashing function learning.

Although the aim of hashing learning is to achieve discrete hash codes, the discrete constraints lead to mixed integer optimization problems, which are generally NP-hard. Therefore, most existing hashing methods usually relax the discrete constraints into a continuous alternative to simplify the optimization, and then the sign function or thresholds is used to turn real values into the approximate discrete hash codes. However, the approximate hash codes are usually suboptimal and thus the effectiveness of the final hash codes is affected. Therefore how to decrease the quantization error and achieve optimal discrete hash codes are critical for hashing learning.

Recent studies focus on learning hashing codes and hashing function simultaneously. The aim of these studies is to make the learned hashing function for obtaining the optimal discrete binary codes which can better approximate the learned hashing codes. Existing discrete hashing methods can be categorized into two main categories: the discrete hash codes which can be achieved by preserving the original similarity, and the discrete hash codes which can be achieved by regressing each hash code to its corresponding class label. Discrete graph hashing [26], Supervised discrete hashing [34], cross-modality sequential discrete hashing (CSDH) [45] and discrete Collaborative Filtering (DCF) [46] are classified into the former category, and supervised discrete hashing (SDH), fast supervised discrete hashing [47] and semi-supervised multi-view discrete hashing [48] are classified into latter category. Discrete graph hashing directly learns the discrete binary codes using a graph-based unsupervised hashing model, and the neighborhood structure of original data can be preserved in hash space. Supervised Hashing discrete presents a joint optimization framework in which the similarity matrix of the pairwise similarity information between the training data is leveraged and the binary constraints are preserved during the optimization, and then the hash function can be achieved by training some binary classifiers. Cross-modality sequential discrete hashing learns the unified hash codes by using a sequentially discrete optimization strategy in which the hash functions are learned simultaneously. Discrete Collaborative Filtering (DCF) aims to minimize the quantization loss during discrete binary codes learning. Meanwhile, the discrete binary hash codes are required to be balanced and uncorrelated to make the learned discrete binary hash codes more informative and compact. Supervised Discrete Hashing utilizes label information by a least squares classification which regresses each hash code to its corresponding label while the hash functions are learned from the directly achieved hash codes. Similarly, to leverage the label information, fast supervised discrete hashing regresses each label to its corresponding hash code. Semi-supervised multi-view discrete hashing minimizes the joint hashing learning model, in which the loss jointly on multi-view features when using relaxation on learning hashing codes is minimized; the statistically uncorrelated multi-view features for generating hash codes is explored; and a composite locality can be preserved in hamming space.

Inspired by the idea of the discrete hashing learning, we propose a novel supervised discrete discriminant hashing framework in this paper. To make the learned discrete hash codes to be optimal for classification, the learned hashing framework aims to maximize the similarity of the same class discrete hash codes and minimize the similarity of the different class discrete hash codes, simultaneously. To this end, we learn a robust similarity metric by leveraging the label information of the training data. Furthermore, a group of hash functions are simultaneously optimized to fit the directly learned binary hash codes in the learned hashing framework. To emphasize the main contributions of this paper, the advantages of the proposed supervised discrete discriminant hashing framework can be summarized as follows:

(1) To make the learned discrete hash codes to be optimal for classification, a novel robust similarity metric is developed in the proposed supervised discrete discriminant hashing approach. We utilize leverage the label information of the original training data to learn a robust similarity metric such that the learned similarity matric can make the similarity of the same class discrete hash codes maximized and the similarity of the different class discrete hash code minimized. Thus, the discriminant information of the training data can be incorporated into the learning framework and the learned discrete hash codes are optimal for classification.
(2) To make the learned hash function for achieving optimal approximate discrete hash codes, the hash functions are optimized based on the directly learned discrete hash codes. A hash functions learned regular term is embedded in the proposed supervised discrete discriminant hashing framework and thus the hash functions can be optimized by the directly learned hash codes.