Learning Label Preserving Binary Codes for Multimedia Retrieval: A General Approach

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Learning-based hashing has received a great deal of research attentions in the past few years for its great potential in fast and accurate similarity search among huge volumes of multimedia data. In this paper, we present a novel multimedia hashing framework, termed as Label Preserving Multimedia Hashing (LPMH) for multimedia similarity search. In LPMH, a general optimization method is used to learn the joint binary codes of multiple media types by explicitly preserving the semantic label information. Compared with existing hashing methods, which are typically developed under and thus restricted to some specific objective functions, the proposed optimization strategy is not tied to any specific loss function, and can easily incorporate bit balance constraints to produce well-balanced binary codes. Specifically, our formulation leads to a set of Binary Integer Programming (BIP) problems that have exact solutions both with and without the bit balance constraints. These problems can be solved extremely fast and the solution can easily scale up to large-scale datasets. In the hash function learning stage, the boosted decision trees algorithm is utilized to learn multiple media-specific hash functions that can map heterogeneous data sources into a homogeneous Hamming space for cross-media retrieval. We have comprehensively evaluated the proposed method using a range of large-scale datasets in both single-media and cross-media retrieval tasks. The experimental results demonstrate that LPMH is competitive against state-of-the-art methods in both speed and accuracy.

CCS Concepts:
• Information systems → Learning to rank; Top-k retrieval in databases; Multimodal and multimodal retrieval;
• Computing methodologies → Visual content-based indexing and retrieval; Supervised learning;

Additional Key Words and Phrases: Learning to hash, supervised learning, multimedia retrieval, large-scale similarity search, discrete optimization, binary integer programming

Reference format:

1 INTRODUCTION

There has been an unprecedented growth of multimedia data on the Internet, due to the rapid advancement of mobile and information technologies, as well as the increasing popularity of social network websites. As such, searching for relevant multimedia content such as images, texts, or videos among these huge volume data repositories turns out to be a very challenging task. Hashing, also know as binary coding, has been widely recognized as a viable solution to such large-scale information retrieval problems [7, 12, 25, 34, 43, 48]. In fact, encoding high dimensional data representations into compact binary codes enjoys some compelling benefits, such as reduced storage overhead, faster distance computation (i.e. Hamming distance), and hash table-based sublinear search [35]. These nice properties of hashing make it possible to search for similar content in large databases with very fast speed that is inconceivable otherwise.

This work is supported by the NASA, under grant NNX15AV40A.
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To Appear in ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM).
Hashing can be generally categorized as single-media hashing and cross-media hashing, with the former focusing on searching among single-modal data (e.g., images), and the latter focusing on enabling comparisons between heterogeneous data representations (e.g., images and texts). In fact, when searching for information on a topic, it’s often desirable to simultaneously return multiple media types, such as images, videos, and text documents, which provide complementary information to each other. In this paper, we investigate the hashing problem in the presence of multiple media types, where both single-media retrieval and cross-media retrieval are concerned.

In light of the inherent speed and storage advantages of binary hashes, the existing hashing research has been mainly focused on improving the accuracy of the search [3, 7, 30, 50]. In this spirit, recent data-dependant hashing algorithms [12, 19, 27, 30, 36, 42] are gaining more popularity over the random hashing method [7] because they can take advantage of the training data to learn more compact and discriminative hash codes. In data-dependent hashing, the hash codes are typically learned by preserving certain intra-media or inter-media similarity measures and solving optimization problems which either have binary constraints or involve discontinuous and non-convex components (e.g., the sign function). Many existing algorithms try to solve a continuous version of the original problem by either relaxing the discrete constraints [31, 38, 42] or finding continuous approximations [18, 23, 27, 30]. However, such hashing schemes are subject to accumulated quantization errors and the resultant hash code quality tends to deteriorate with increasing code length [29].

To improve the quality of learned hash codes, there have been some efforts in solving the binary-constrained discrete optimization problems directly, leading to the family of discrete hashing algorithms. Representative works include Discrete Graph Hashing (DGH) [29], FastHash [25] and Column Sampling Discrete Hashing (COSDISH), etc. The quality of the hash codes generated by those algorithms is found to be much better than that of relaxed solutions [25, 29]. Nevertheless, most of those algorithms have high computational costs because they are designed to preserve pairwise similarities which often lead to NP-hard Binary Quadratic Programming (BQP) problems. The complexity of the approximate solutions to those BQP problems are typically at least \( O(n^2) \), making them not scalable to large-scale datasets. Moreover, these discrete methods have been proposed for single-media hashing and are not directly applicable for multimedia hashing.

To address the aforementioned limitations, we propose a scalable discrete hashing framework for multimedia data, termed as Label Preserving Multimedia Hashing (LPMH) hereinafter. Instead of dealing with the pairwise affinities among training samples, we explicitly optimize the binary hash codes to preserve the instance-wise semantic labels. Such an initiative can be highly computationally efficient, as the effective size of the training set is kept at \( O(n) \), in contrast with the \( O(n^2) \) training pairs in the pairwise case. We realize that a similar classification-based method has been used for single-media hashing in the recent work Supervised Discrete Hashing [36]. However, there are several limitations in SDH that differentiate it from our work. Firstly, since SDH is formulated with respect to certain loss functions, its optimization steps are tightly coupled with the specific form of loss function and thus it’s not straightforward to study the trade-offs between different types of losses. Secondly, it’s unclear how the Discrete Cyclic Coordinate descent (DCC) algorithm in SDH can be combined with the widely-used bit balance constraints [12, 40] to generate balanced binary bits. Finally, the interleaved learning of binary codes and hash functions makes SDH inappropriate for multimedia settings.

The proposed LPMH adopts a flexible two-stage learning framework for joint binary codes and media-specific hash functions. Specifically, LPMH first learns the binary codes by iteratively solving a series of unconstrained Binary Integer Programming (BIP) subproblems. Unlike most of the existing methods, which are tightly coupled with certain objective functions, the proposed discrete
optimization method is a unified solution to different types of loss functions. Additionally, the proposed solution can easily incorporate bit balance constraints, which have been found to be quite effective in generating better binary codes in the hashing literature [16, 40]. For out-of-sample extension, the joint binary codes are used as the common labels to coordinate the learning of multiple media-specific hash functions. To sum up, we highlight the major contribution of this paper as follows:

- We propose a general approach to solve the classification-based binary code inference problem. We formulate the binary code optimization problem as a series of binary integer programming subproblems, and show that they have a simple and unified analytic solution irrespective of the type of loss function used.
- Our formulation can be easily combined with bit balance constraints and we provide a simple yet effective solution to the constrained optimization problem with linear time complexity. Additionally, we give proofs of the optimality of the proposed solution.
- As the first work that combines classification-based discrete optimization with the two-stage learning framework, the proposed method is both scalable and flexible. In particular, the method is equally optimized for single-media and cross-media similarity search.
- We extensively evaluate the proposed algorithm in both single-media and cross-media retrieval tasks, and we have separately compared with the state-of-the-arts of both settings. The experimental results indicate that our algorithm compares favorably against the state-of-the-arts across a number of large-scale datasets and multiple retrieval benchmarks.

The remaining of the paper is organized as follows. We first review the related works in Section 2. The proposed Label Preserving Multimedia Hashing approach is introduced and discussed in detail in Section 3. We extensively evaluate our algorithm and discuss the experimental results in Section 4, followed by the conclusion in Section 5.

2 RELATED WORK

Traditionally, single-media and cross-media retrieval have been studied separately in the literature. Since the proposed method is relevant to both, we review the related works in those two areas separately as follows.

2.1 Single-Media Retrieval

The earliest hashing methods are mostly unsupervised, and they are designed to preserve the similarities defined on the original feature space (e.g. based on Euclidean distance). Examples in this category include Spectral Hashing (SH) [40], Binary Reconstructive Embedding (BRE) [18], Iterative Quantization (ITQ) [12], Anchor Graph Hashing (AGH) [31], etc.

Quantization-based methods have also achieved competitive performances in similarity search, especially in Euclidean distance-based descriptor search tasks. Typically, quantization methods can avoid directly computing the Euclidean distances by using dictionary lookups, and very good approximations can be achieved with enough dictionaries. The most notable works are Product Quantization (PQ) [14] and its variants, such as Optimized Tree Quantization (OTQ) [2], Optimized Product Quantization (OPQ) [11], Sparse Composite Quantization (SQ) [46], and Composite Quantization (CQ) [45].

Both unsupervised hashing and quantization approaches are mostly designed for approximate nearest neighbor search in the metric space and are not tailored for similarity search at the semantic level. In contrast, supervised hashing methods are proposed to directly target semantic similarities by incorporating supervised label information.
It has been verified in various studies that the inclusion of supervised label information can significantly boost the quality of hashing-based semantic similarity search [25, 30]. A number of supervised hashing algorithms have been proposed recently including Minimal Loss Hashing (MLH) [34], Kernel-based Supervised Hashing (KSH) [30], Two-Step Hashing (TSH) [26], Discrete Supervised Hashing (DISH) [44], Kernel-based Supervised Discrete Hashing (KSDH) [37], FastHash [25], Column Sampling based Discrete Supervised Hashing (COSDISH) [16], Supervised Ranking Hash (SRH) [23], Supervised Discrete Hashing (SDH) [36], etc.

These supervised algorithms can be classified as discrete or continuous in terms of optimization techniques. Continuous methods either drop the binary constraints (e.g. SH [40]) or approximate the sign function using continuous functions (e.g. KSH, BRE [18]) during the optimization process, followed by binary quantization to obtain the hash codes. Such procedures typically lead to accumulated quantization errors. Discrete hashing algorithms (e.g. DGH [29], FastHash [25], SDH [36], RoPH [10]), on the other hand, directly solve the binary programming problem, and therefore can avoid large quantization errors and lead to better hash codes. However, discrete hashing algorithms usually need to solve BQP problems, which are known to be NP-hard.

There are several types of objective functions for hash learning, namely, pairwise loss, triplet ranking loss and classification-based loss. The majority of existing hashing algorithms are based on pairwise similarity objectives [18, 24–26, 29, 30, 34, 40]. The pairwise labels can be obtained from metric distances or semantic labels. Such objective functions are natural as the hash codes are expected to preserve certain similarity measures between data points. Triplet-based objectives are also exploited in the literature (e.g. triplet-based deep hashing [20]). Triplet ranking losses are typically formulated to preserve relative ranking orders among data triplets. Pairwise and triplet losses usually need to deal with $O(n^2)$ data pairs or $O(n^3)$ data triplets given a training set of $n$ samples, which makes space and time complexity of training at least $O(n^2)$ or $O(n^3)$. In comparison, classification-based methods (e.g. VDSH [49], SDH [36]) only need to deal with $O(n)$ training samples and thus can scale to large datasets more easily.

2.2 Cross-media Retrieval

Cross-media retrieval research needs to deal with heterogeneous feature spaces and it begins to pick up attention more recently. The earliest work on cross-media hashing is arguably Cross-Modal Similarity Sensitive Hashing (CMSSH) [3], which was originally proposed for cross-representation shape retrieval and multi-modal medical image alignment applications. A number of new methods were proposed soon after CMSSH, including Cross-View Hashing (CVH) [19], Co-Regularized Hashing (CRH) [50], and Multimodal Latent Binary Embedding (MLBE) [51] etc. Many earlier cross-media hashing methods, however, are limited either by unsatisfactory retrieval performance, or by the poor scalability in training (e.g. CMSSH) or out-of-sample extension (e.g. MLBE).

A few efforts have been made to tackle the scalability issues. For example, Inter-Media Hashing (IMH) [38] extracts correlation among large-scale heterogeneous data sources using both labeled and unlabeled data. Semantic Correlation Maximization (SCM) [42] extends the classical Canonical Correlation Analysis (CCA) with semantic label information and scales to large datasets by avoiding the explicit computation of pairwise affinities among training samples; Semantic Topic Multimodal Hashing (STMH) [39] learns a common feature subspace from multimedia semantic concepts, and encodes a hash bit by examining the existence of a concept.

To improve the cross-media retrieval accuracy, the cross-media hashing research has been developing in several different directions. A few research efforts take advantage of matrix factorization to capture the latent structure of multimedia data, such as Collective Matrix Factorization Hashing (CMFH) [9], Supervised Matrix Factorization Hashing (SMFH) [28] and Latent Semantic Sparse
Hashing (LSSH) [52]. Some other works learn the hash codes based on features’ ranking orders. For example, Cross-modal Ranking Subspace Hashing (CMRSH) [21] and Linear Subspace Ranking Hash (LSRH) [22] learn ranking-based hash functions by finding the optimal linear subspaces of different feature spaces to maximally preserve the features’ ranking orders.

There are also works using quantization techniques for cross-media hashing. For instance, Composite Correlation Quantization (CCQ) [32] jointly finds correlation-maximal mappings that transform data from different media types into an isomorphic latent space. Additional quantization methods include Alternating Co-Quantization (ACQ) [13] and Cross-Modal Collaborative Quantization (CMCQ) [47] etc.

Another emerging direction in cross-media hashing is based on deep learning. In contrast to traditional hashing methods, in which the focus is to learn good hash codes given fixed feature representations, deep cross-media hashing methods study how to combine the representation learning and hash learning in a seamless framework. Leading performances have also been reported in recent deep cross-media hashing methods, such as Multimedia Neural Network (MMNN) hashing [33], Deep Cross-Modal Hashing (DCMH) [15], Correlation Hashing Network (CHN) [4], Collective Deep Quantization (CDQ) [5], etc.

Recently, two-step hashing approaches which decouple binary code and hash function learning have been used in cross-media search. The most notable approach is Semantics-Preserving Hashing (SePH) [27], which first obtains the joint binary codes by minimizing the KL-divergence between the similarity distribution and the semantic distribution of hash codes and then uses logistic regression to learn hash functions for each media. The performance of SePH has been reported to significantly outperform most state-of-the-art cross-media hashing algorithms.

3 LABEL PRESERVING MULTIMEDIA HASHING

3.1 Problem Definition

Suppose we have a training set of $N$ instances, denoted as $S = \{s_1, s_2, \cdots, s_N\}$ with $s_n$ being the $n^{th}$ instance. We consider the case that an instance $s_n$ can be associated with one or multiple media types and denote the feature vector of the $m^{th}$ media type as $x_m^n \in \mathbb{R}^{d_m}$, where $1 \leq m \leq M$ and $M$ is the number of media types. We assume the training set belong to $C$ different classes and each instance has a class label, denoted as an indicator vector $t_n \in \{0, 1\}^C$, where a non-zero entry indicates the instance belongs to the corresponding class. Our objective is to learn the $L$-bit label-preserving binary codes $B = [b_1, b_2, \cdots, b_N] \in \{-1, 1\}^{L \times N}$, as well as a set of media-specific hash functions $\mathcal{H} = \{h^1(x), h^2(x), \cdots, h^M(x)\}$ such that new data samples from heterogeneous media types can be mapped to a common Hamming space. We explicitly decouple the binary code inference and the hash function learning stages using a two-step hashing framework, as will be explained in detail in this section.

3.2 Binary Code Optimization

As indicated by recent studies [25, 36, 49], high-quality binary codes should also be good feature representations for classification tasks. Therefore, we explicitly preserve the semantic label information in the binary code learning stage. Formally, the general label-preserving binary code learning problem can be written as

$$\min_{B, f} \sum_{n=1}^{N} \mathcal{L}(f(b_n), t_n) + \Omega(f),$$

subject to $B \in \{-1, 1\}^{L \times N}$.
where \( \mathcal{L}(y, t) \) could be any proper loss function defined with respect to a prediction \( y \) and a target label \( t \), \( f(\cdot) \) is a decision function that maps an input to a decision output with the same dimensionality as the label vector, and \( \Omega(f) \) is the regularization term.

Generally speaking, a better feature representation would need a simpler classifier to achieve the same level of classification performance. In order for the binary codes to be the best for classification, we choose \( f(\cdot) \) to be the simplest decision function; that is, the linear function

\[
f(x) = W^T x,
\]

where \( W = [w_1, w_2, \cdots, w_C] \in \mathbb{R}^{L \times C} \) is the linear model coefficient matrix. Therefore, we focus on the following optimization problem

\[
\min_{B, W} \frac{1}{N} \sum_n \mathcal{L}(W^T b_n, t_n) + \frac{\mu}{2} ||W||_F^2 ,
\]

\[
\text{s.t. } b_n \in \{-1, 1\}, n = 1, 2, \cdots, N,
\]

where \( \mu \) is the regularization coefficient and \( || \cdot ||_F \) is the Frobenius norm. Note that we have used the averaging form of the loss term to make the regularlization coefficient independent of the training size.

With both continuous and discrete decision variables, (3) is a Mixed Integer Programming (MIP) problem that is typically highly non-convex and difficult to solve. The recent work [36] has a similar formulation as (3). However, [36] introduces the binary codes as auxiliary variables to replace the binary hash functions and has an additional code-fitting term which makes the optimization process more complex and specific to the choice of \( \mathcal{L}(\cdot, \cdot) \). In the following, we show that the explicit optimization of the binary codes in (3) can be much more efficient and leads to more general solutions.

Specifically, we solve \( W \) and \( B \) alternately by fixing the other. First consider fixing the binary codes \( B \). The optimization with respect to \( W \) becomes a continuous optimization problem that can be conveniently solved using well-established Stochastic Gradient Descent (SGD) (for differentiable loss functions) or subgradient descent (for non-differentiable loss functions) methods, and the update rule for the weight matrix is

\[
W \leftarrow W - \eta(\nabla \mathcal{L}_n(W) + \mu W)
\]

where \( \mathcal{L}_n(W) \) is short for \( \mathcal{L}(W^T b_n, t_n) \), \( \nabla \) is the gradient/subgradient operator, and \( \eta \) is the step size. Note that (4) can also be replaced with a batch update rule where the update directions are averaged over the gradients/subgradients of a batch of samples.

Now consider fixing \( W \). Problem (3) then becomes a binary integer programming (BIP) problem, which is still hard to solve given the \( O(2^{L \times N}) \) solution space. Motivated by [25], we propose to iteratively solve each bit by fixing all the other bits. In fact, \( \mathcal{L}(\cdot, \cdot) \) is only a function of the \( l^{th} \) bit when fixing all the other bits, and we denote it as \( \kappa_{nl}(\cdot) \)

\[
\kappa_{nl}(b_{nl}) = \mathcal{L}(b_{nl}; b_{n\\slash l}, W, t_n),
\]

where \( b_{nl} \) is the \( l^{th} \) bit of the \( n^{th} \) sample’s binary code, and \( b_{n\\slash l} \) denotes the sample’s binary code vector by excluding the \( l^{th} \) bit. We have used the subscript \( nl \) here to identify \( \kappa_{nl}(\cdot) \) since each function is defined with respect to a specific sample and binary bit. Then our problem can be simplified as

\[
\min_{b_{nl} \in \{1, -1\}} \sum_n \kappa_l(b_{nl}).
\]
Here we have omitted the constant terms (i.e. independent of $B$) and multiplicative coefficients that do not affect the solution to the problem.

With the following proposition, we show that the problem in (6) can be written as a general linear BIP problem with a simple analytic solution.

**Proposition 1.** For any loss function $\kappa(x)$ defined on the binary input $x \in \{1, -1\}$, there exists a linear function $\gamma(x)$ equal to $\kappa(x)$, and it's defined as

$$\gamma(x) = \frac{\kappa(1) - \kappa(-1)}{2} x + \frac{\kappa(1) + \kappa(-1)}{2}.$$  

(7)

**Proof.** The above proposition can be proven by evaluating both functions at all possible inputs. Since there are only two possible inputs 1 and -1, they can be easily verified as follows:

$$\gamma(1) = \frac{\kappa(1) - \kappa(-1)}{2} + \frac{\kappa(1) + \kappa(-1)}{2} = \kappa(1)$$

$$\gamma(-1) = -\frac{\kappa(1) - \kappa(-1)}{2} + \frac{\kappa(1) + \kappa(-1)}{2} = \kappa(-1)$$

This concludes that $\kappa(x) = \gamma(x)$. □ 

Applying the above proposition to problem (6) leads to the following form

$$\min b^T c, \quad \text{s.t. } b, l \in \{-1, 1\}^N,$$  

(8)

where $b, l$ is the $l^{th}$ row vector of $B$, and the constant vector $c_l$ is defined as

$$c_l = \left[ \frac{\kappa_1(1) - \kappa_1(-1)}{2}, \ldots, \frac{\kappa_N(1) - \kappa_N(-1)}{2} \right]^T.$$  

(9)

The problem in (8) has a simple closed-form solution

$$b^*_l = \text{sgn}(-c_l)$$  

(10)

In sum, the major steps for learning label preserving binary codes are presented in Algorithm 1. Note that our discussion so far is not tied to any specific loss function, and thus the presented algorithm is a general one. Generally speaking, any proper loss functions can be used in our algorithm, but we only discuss a few commonly used loss functions in the following.

**Cross-Entropy Loss** The cross-entropy loss is a probabilistic loss function frequently used in classification tasks

$$L^{(ce)}(y, t) = -\sum_i y_i \ln t_i.$$  

(11)

**Square Loss** The squared loss imposes a squared error on the difference between the prediction and the target and can be used for both classification and regression tasks.

$$L^{(se)}(y, t) = ||y - t||^2.$$  

(12)

**Logistic Loss** The logistic loss function measures the degree of fit between the prediction and the target and is mostly used in regression tasks. It’s defined as

$$L^{(log)}(y, t) = \sum_i \log(1 + e^{-y_i t_i}).$$  

(13)

**Hinge Loss** The hinge loss is typically used for max-margin classification, most notably for SVMs. It’s defined as

$$L^{(h)}(y, t) = \sum_i \max(0, 1 - y_i t_i).$$  

(14)
Algorithm 1: Label Preserving Multimedia Hashing

Input: Data $X$ and their semantic labels $T$.
Output: Binary codes $B$ and weight matrix $W$.

Initialization: Randomly initialize $B$ and $W$

repeat
  repeat
    Estimate the gradient/subgradient of $L(\cdot, \cdot)$ w.r.t. $W$ over a sample or a mini-batch
    Update $W$ in the gradient/subgradient descent direction (e.g. using equation (4))
  until convergence
  repeat
    for $l = 1, 2, \cdots, L$ do
      Compute $c_l$ as defined in (9)
      Solve the $l^{th}$ row of $B$ according to (10)
    end
  until convergence
until convergence or maximum iteration reached

The gradient/subgradient of those loss functions can be computed easily as follows

\begin{align}
\nabla L_n^{(ce)}(W) &= b \cdot (t - e^t/||e^t||)_T^T \\
\nabla L_n^{(se)}(W) &= b \cdot (y - t)^T \\
\nabla L_n^{(lg)}(W) &= b \cdot (t \circ I(y \circ t < 1))^T \\
\nabla L_n^{(hg)}(W) &= b \cdot (\text{diag}^{-1}(1 + t) \cdot y)^T,
\end{align}

where ‘$\circ$’ is the element-wise Hadamard product, $I(\text{condition})$ is the indicator function that outputs 1 when the condition holds and 0 otherwise, and $\text{diag}(v)$ is the diagonal matrix with $v$ as its diagonal entries.

3.3 Bit Balance Constraints

The bit balance constraint forces each bit position to have an equal number of 1s and −1s (or 0s), and this has been found to be beneficial to the quality of binary codes. As a result, it has been widely used in the hashing literature [16, 31, 40, 44]. With the bit balance constraint, problem (3) can be rewritten as

\begin{equation}
\min_{b, W} \frac{1}{N} \sum_n L(W^T b_n, t_n) + \frac{\mu}{2} ||W||^2_F, \\
\text{s.t. } B1 = 0, \\
B \in \{-1, 1\}^{L \times N}.
\end{equation}

The first constraint is the bit balance constraint, where $1$ and $0$ denote the vector of all ones and zeros respectively. Such a constraint often makes the binary optimization problem more complex. Therefore, some recent hashing methods [22, 27, 36] simply ignore it.

The steps for solving the bit balanced binary optimization problem remain the same except that the sub-problem in (8) becomes

\begin{equation}
\min_{b \in \{-1, 1\}^N} \varrho(b) = c^T b + \lambda|1^T b|,
\end{equation}
where $\lambda > 0$ controls the weight of the bit balance constraint, and the resultant hash codes could be perfectly balanced with sufficiently large $\lambda$. Note that we have omitted the subscripts to make the following discussion clearer.

Clearly, problem (17) no longer enjoys any closed-form solutions, and the complexity of the brute-force search would be $O(2^N)$. In the following proposition, we propose an effective solution to this problem and prove its optimality.

**Proposition 2.** There exists an algorithm that finds the optimal solution to problem (17) in at most polynomial time.

**Proof.** We derive the optimal solution by construction. Specifically, we search for the optimal solution of (17) by starting from the solution in (10). First consider the case when $b^*$ is balanced (i.e. $|1^T b^*| \leq 1$), then $b^*$ is also the solution to (17) because it minimizes both terms of $g(b)$.

If $b^*$ is not balanced (i.e. $|1^T b^*| > 1$), we need to flip some bits to decrease the second term of $g(b)$. Depending on the sign of $1^T b^*$, one may flip positive or negative bits to decrease the value of the second term. For instance, when $1^T b^* > 1$, flipping a bit from 1 to -1 would decrease the second term by $2\lambda$. Note that, however, the decrease of the second term doesn’t necessarily decrease the overall value of the objective function $g(b)$, because flipping any bit $\hat{b}_i$ of $b$ would increase the value of the first term by $2|c_i|$. Therefore, the net decrease of $g(b)$ caused by flipping the $i$th bit is

$$\delta_i = 2\lambda - 2|c_i|.$$

In order to minimize $g(b)$, one can simply pick the bit with the maximum $\delta_i$ at each step until there doesn’t exist any bit that satisfies $\delta_i > 0$, or when the code has become balanced. The optimality of the obtained solution can be verified easily by noticing that $g(b)$ no longer decreases with any bit flips in both stop conditions.

The constructive process above consists of up to $O(N)$ bit flips, and each bit flip involves a max operation (i.e. selecting the maximum $\delta_i$) with $O(N)$ complexity. Therefore, the above algorithm has a $O(N^2)$ time complexity, which concludes the proof. □

While the above proposition alludes to a simple iterative algorithm that flips one bit at a time, the actual implementation can take advantage of the independence among multiple flips to arrive at the optimal solution in one step. The pseudo-algorithm for our implementation is summarized in Algorithm 2. In fact, the complexity of Algorithm 2 is only $O(N)$ because each line can be computed in no more than $O(N)$ time\(^1\).

To enable or disable the bit balance constraints, one can simply switch between equation (10) and Algorithm 2 while solving for one row of the code matrix (i.e. line 10 of Algorithm 1). Note that the time complexity of the entire algorithm remains unchanged with the bit balance constraints, as a result of the proposed $O(N)$ solution in Algorithm 2.

### 3.4 Algorithm Complexity

It’s not hard to verify that the complexity of the entire discrete optimization algorithm is linear with respect to the training size $N$. Here we analyze its computational complexity in detail. Solving for $W$ typically involves going over the training set a number of times, and its complexity can be denoted as $O(I_w N)$, where $I_w$ is the number of sweeps. The complexity for solving the binary code matrix once is $O(LN)$, which leads to the complexity of $O(I_b LN)$ when iterating for $I_b$ times. Therefore, the complexity for one outer loop in Algorithm 1 is $O(I_w N + I_b LN)$. Let $I_o$ be the number of outer iterations, then the overall complexity of Algorithm 1 adds up to $O((I_w + I_b L)I_o N))$.

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\(^1\)The $O(N)$ algorithm for line 6 is QuickSelect.
ALGORITHM 2: Solving Balanced Binary Codes

**Input:** Constant vector $c$, weight $\lambda$.
**Output:** Balanced binary codes $b$.

1. Initialize $b \leftarrow \text{sgn}(-c)$
2. Compute the sign of unbalance $s \leftarrow \text{sgn}(1^T b)$
3. Compute the level of unbalance $m \leftarrow \lceil |1^T b|/2 \rceil$
4. Find the set of candidate bits $\mathcal{A} \leftarrow \{b_i | b_i = s \text{ and } |c_i| < \lambda \}$
5. **if** $|\mathcal{A}| > m$ **then**
   6. Find $m$ bits with the smallest $c_i$s in $\mathcal{A}$
   7. Flip the signs of those $m$ bits
5. **else**
   8. Flip the signs of all the bits in $\mathcal{A}$
   9. **end**

We have empirically studied the convergence of the algorithm, and the results on the ImageNet dataset are illustrated in Figure 1. The results on the other datasets are very similar, and therefore they are omitted. It can be noted from the results that the algorithm converges very fast. And we have empirically fixed the maximum iteration number: $I_w$, $I_b$, and $I_o$ to 20, 2, and 2 respectively throughout our experiments. In sum, the linear complexity and fast convergence of the proposed optimization algorithm make the training process highly efficient and scalable, as will also be evidenced in the experiments.

![Image](image1.png)  
**Fig. 1.** An empirical study of the convergence of the discrete optimization algorithm. (a) The objective value as function of the iteration number $I_b$ while solving for the binary codes. (b) The objective value as a function of the number of sweeps $I_w$ while learning the projections $W$. (c) The overall objective value with respect to the number of outer iterations $I_o$ in Algorithm 1. The results are obtained for the 64-bit optimizer on the ImageNet dataset with the cross-entropy loss function, and the results on the other datasets and with other settings are very similar.

### 3.5 Hash Function Learning

We have obtained the hash codes that preserve the semantic label information for the training set $S$. We also need to learn a set of hash functions, one for each media type, so that new data from different media types can be encoded into a common Hamming space to support cross-media search. In fact, as pointed out by [27], once the hash codes have been obtained, the hash function learning can be modeled as a set of classification problems, with each hash bit corresponding to
one binary classifier. Specifically, each bit of the obtained hash codes can be used as the binary label to train a binary classifier, which is open to a wide range of solutions such as SVM, logistic regression, decision trees etc.

For the proposed method, we choose to use the boosted decision trees (BST) and the reasons for such choice are threefold: 1) BSTs provide good nonlinear mapping capabilities and better generalization capabilities than linear methods; 2) the testing could be much more efficient than other nonlinear mapping methods since it only involves value comparisons; 3) we use the efficient implementations proposed in [1] and it speeds up the training and scales well to large-scale datasets. Formally, each binary bit is determined by the following hash function

\[ h_t(x) = \text{sgn}\left( \sum_{i=1}^{T} \alpha_t D_t(x) \right), \]

where \( T \) is size of the decision trees ensemble, \( D_t : \mathbb{R}^d \mapsto \{-1, 1\} \) is the \( t^{th} \) decision tree, and \( \alpha_t \) is a function of the error rate of \( D_t \), defined as \( \alpha_t = \ln(1/\epsilon_t - 1) \). In our implementation, we have fixed the depth of the decision trees to 4, and the number of boosting iterations is to 200. Note that we have omitted the media-specific super script for ease of presentation, and the solution is applicable to different media types (i.e. \( X^{(m)}, m = 1, \cdots, M \)) to obtain the media specific hash function.

Briefly, a sequence of binary decision trees is learned by adapting the weights of the training samples based on whether they’re correctly classified by the previous one. The learning of each decision tree is essentially finding a set of decision stumps and more details of this classic ensemble learning approach can be found in [1].

4 EXPERIMENTS

To evaluate the proposed algorithm, we have conducted extensive experiments on a range of widely used datasets, including both single-media datasets (i.e. CIFAR-10\(^2\), SVHN\(^3\) and ImageNet \(^8\)) and multimedia datasets (i.e. Labelme \(^4\), MIRFlickr \(^5\), and NUSWIDE \(^6\)). A brief view of the statistical information of these datasets are summarized in Table 1.

<table>
<thead>
<tr>
<th>Name</th>
<th>Type</th>
<th>Features</th>
<th>Concepts</th>
<th>Size</th>
</tr>
</thead>
<tbody>
<tr>
<td>CIFAR-10</td>
<td>Single-media</td>
<td>512D GIST</td>
<td>N/A</td>
<td>10</td>
</tr>
<tr>
<td>SVHN</td>
<td>Single-media</td>
<td>512D GIST</td>
<td>N/A</td>
<td>10</td>
</tr>
<tr>
<td>ImageNet</td>
<td>Single-media</td>
<td>2048D CNN</td>
<td>N/A</td>
<td>1000</td>
</tr>
<tr>
<td>Labelme</td>
<td>Multimedia</td>
<td>512D GIST</td>
<td>245D TOF</td>
<td>8</td>
</tr>
<tr>
<td>MIRFlickr</td>
<td>Multimedia</td>
<td>150D EH</td>
<td>1075D TOF</td>
<td>24</td>
</tr>
<tr>
<td>NUS-WIDE</td>
<td>Multimedia</td>
<td>500D BOVW</td>
<td>1000D TOF</td>
<td>81</td>
</tr>
</tbody>
</table>

Since the proposed method handles multiple media types in a homogeneous way, it’s equally optimized for single-media and cross-media retrieval tasks. Therefore, we evaluate its performance

\(^2\)https://www.cs.toronto.edu/~kriz/cifar.html
\(^3\)http://ufldl.stanford.edu/housenumbers/
\(^4\)http://people.csail.mit.edu/torralba/code/spatialenvelope/
\(^5\)http://press.liacs.nl/mirflickr/
\(^6\)http://lms.comp.nus.edu.sg/research/NUS-WIDE.htm
on both applications. Specifically, three types of retrieval tasks are considered in our experiments, that is, “image query image”, “text query image” and “image query text”. As most of the existing hashing methods are either designed for single-media queries or cross-media queries while not optimized for both, we compare with the state-of-the-arts in each setting separately. In the image retrieval experiments, we have chosen three competitive single-media hashing methods, including FastHash [25], Supervised Discrete Hashing (SDH) [36] and Column Sampling Discrete Hashing [16], as well as two state-of-the-art quantization methods: Product Quantization (PQ) and Composite Quantization (CQ). In the cross-media retrieval settings, we have considered the state-of-the-art cross-modal quantization methods: Composite Correlation Quantization (CCQ) and six competitive cross-modal hashing methods, including Inter-media Hashing (IMH) [38], Latent Semantic Sparse Hashing (LSSH) [52], Collective Matrix Factorization Hashing (CMFH) [9], Semantic Correlation Maximization (SCM) [42], Quantization Correlation Hashing (QCH) [41] and Semantics-Preserving Hashing (SePH) [27]. Most of the compared algorithms have been briefly introduced in Section 2, and the source code for all of the algorithms are kindly provided by the authors; therefore, we are able to run all of them on the same system settings using the suggested parameters (if applicable). Additionally, we have also compared with a few deep cross-media hashing methods [4, 5, 33], which will be discussed in detail in Section 4.2.2.

The proposed LPMH takes two hyper-parameters, that is, the regularization coefficient $\mu$ and the weight of bit balance term $\lambda$, and they are fixed to $\mu = 1$ and $\lambda = 1$ throughout the experiments. The experiments are conducted on a system with Intel Xeon E5-2680 CPU @ 2.4 GHz and 64 GB of memory, and all of the experiment results are averaged over five independent runs unless otherwise specified. We measure the performances of different methods with three widely used retrieval metrics; that is, precision@top-k, precision-recall curves, and mean Average Precision (mAP) [22, 25, 27, 36].

4.1 Image Retrieval

4.1.1 Comparison with all the baselines. We evaluate the image retrieval performance of the proposed LPMH on CIFAR-10, SVHN, and ImageNet. For ImageNet, we first report the results on its 200-class subset of (i.e. ImageNet-2007) while discussing that of the full dataset later. The ImageNet-200 subset contains 110000 images, and it is used because a few baselines cannot be trained on the entire ImageNet dataset due to prohibitive time and memory costs. For each of CIFAR-10, SVHN and ImageNet-200, we randomly sample the same number of images from each class to form a query set of 2000 images, and the rest are used as the training set and database. We define the true neighbors of a query to be those sharing the same class label.

The results of the major evaluation metrics are shown in Table 2. Note that the reported mAP is computed over all retrieved samples, and thus it’s a good indicator of the overall performance of a hashing method. In contrast, the precision of top-100 neighbors is more relevant in scenarios where only the quality of the top returns is concerned. We can observe from those results that the proposed LPMH is competitive against or superior to the baselines at different code lengths. Additionally, we have plotted the precision-recall curve and the precision with varying number of returned neighbors in Figure 2 and Figure 3 respectively. Similarly, the proposed LPMH also generates leading performances in those tests.

It’s worth noting that although quantization methods such as PQ and CQ are good metric distance approximators, they are less effective in semantic retrieval tasks as a result of not being able to take advantage of data labels. In comparison, supervised hashing methods are better at capturing the semantic similarities and therefore can achieve better performances in our test. We also find

https://tiny-imagenet.herokuapp.com/
Table 2. Test results of all the methods in terms of mAP and precision@top-100 on CIFAR-10, SVHN and ImageNet-200. The length of the binary code is varied from 16 bits to 64 bits. The best result for each metric is shown in bold. The proposed LPMH consistently outperforms the baselines in different metrics.

<table>
<thead>
<tr>
<th>Method</th>
<th>CIFAR-10</th>
<th>SVHN</th>
<th>ImageNet-200</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>16 bits</td>
<td>32 bits</td>
<td>64 bits</td>
</tr>
<tr>
<td>mAP</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PQ</td>
<td>0.1731</td>
<td>0.1724</td>
<td>0.1763</td>
</tr>
<tr>
<td>CQ</td>
<td>0.1789</td>
<td>0.1843</td>
<td>0.1865</td>
</tr>
<tr>
<td>FastHash</td>
<td>0.5285</td>
<td>0.5957</td>
<td>0.6389</td>
</tr>
<tr>
<td>COSDISH</td>
<td>0.5662</td>
<td>0.6020</td>
<td>0.6120</td>
</tr>
<tr>
<td>SDH</td>
<td>0.5847</td>
<td>0.6476</td>
<td>0.6859</td>
</tr>
<tr>
<td>LPMH</td>
<td><strong>0.6754</strong></td>
<td><strong>0.7217</strong></td>
<td><strong>0.7359</strong></td>
</tr>
</tbody>
</table>

Precision@Top-100

<table>
<thead>
<tr>
<th>Method</th>
<th>CIFAR-10</th>
<th>SVHN</th>
<th>ImageNet-200</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>16 bits</td>
<td>32 bits</td>
<td>64 bits</td>
</tr>
<tr>
<td>PQ</td>
<td>0.2912</td>
<td>0.2873</td>
<td>0.3175</td>
</tr>
<tr>
<td>CQ</td>
<td>0.3177</td>
<td>0.3201</td>
<td>0.3250</td>
</tr>
<tr>
<td>FastHash</td>
<td>0.5779</td>
<td>0.6225</td>
<td>0.6492</td>
</tr>
<tr>
<td>COSDISH</td>
<td>0.8241</td>
<td>0.8572</td>
<td>0.8750</td>
</tr>
<tr>
<td>SDH</td>
<td>0.5409</td>
<td>0.6119</td>
<td>0.6224</td>
</tr>
<tr>
<td>LPMH</td>
<td><strong>0.6186</strong></td>
<td><strong>0.6611</strong></td>
<td><strong>0.6718</strong></td>
</tr>
</tbody>
</table>

that classification-based hashing methods generally compares more favorably with the pairwise-based discrete hashing methods (e.g. COSDISH and FastHash), which verifies the effectiveness of classification-based hashing methods in capturing the semantic similarities among training samples [36]. Meanwhile, although both SDH and the proposed LPMH are classification-based hashing methods, the proposed LPMH performs much better in most of the benchmarks, thus demonstrating the superiority of the proposed hash learning framework.

Fig. 2. Precision-recall curves with 32-bit hash code on three large-scale image datasets. Larger area under the curve indicates better performance. The proposed LPMH achieves the best overall performance.
Fig. 3. The precision of different methods with varying number of returned neighbors. The results are obtained with 32-bit hash code. The proposed LPMH outperforms all the baselines.

Table 3. Test results of the most competitive methods on the full ImageNet dataset. The methods are trained using the entire 1,281,167 training split. We randomly select 5000 images from the provided validation set as test queries, and the entire training set is used as the database. The mAP and top-k precision (64 bits) are reported. The proposed LPMH scales very well on the million-scale dataset and achieves competitive performances against the other methods.

<table>
<thead>
<tr>
<th>Method</th>
<th>16 bits</th>
<th>32 bits</th>
<th>64 bits</th>
<th>k=100</th>
<th>k=400</th>
<th>k=1600</th>
</tr>
</thead>
<tbody>
<tr>
<td>PQ</td>
<td>0.2405</td>
<td>0.2989</td>
<td>0.3335</td>
<td>0.5253</td>
<td>0.4718</td>
<td>0.3116</td>
</tr>
<tr>
<td>CQ</td>
<td>0.2694</td>
<td>0.3179</td>
<td>0.3488</td>
<td>0.5518</td>
<td>0.4956</td>
<td>0.3317</td>
</tr>
<tr>
<td>SDH</td>
<td>0.2819</td>
<td>0.4173</td>
<td>0.5462</td>
<td>0.5149</td>
<td>0.5138</td>
<td>0.4255</td>
</tr>
<tr>
<td>LPMH</td>
<td>0.3419</td>
<td>0.4715</td>
<td>0.5853</td>
<td>0.5588</td>
<td>0.5576</td>
<td>0.4582</td>
</tr>
</tbody>
</table>

4.1.2 Large-scale retrieval on the full ImageNet. We use the ImageNet dataset from ILSVRC2012, and it contains more than 1.2 million fully labeled training images belonging to 1000 object classes. The ImageNet dataset comes with 50,000 validation images and the corresponding ground-truth labels. Our method can be trained very efficiently on the whole training set, while some of the baselines are intractable. Therefore, we only retain the most scalable baselines for comparison. For testing, we randomly select 10% (i.e. 5000) queries from the validation set and use the entire training set as the database. The results of this experiment are shown in Table 3. As can be observed from the results, our LPMH performs consistently better than both SDH and the quantization methods. We also observe that the performance gap between the quantization methods and the supervised hashing methods are much smaller than that on CIFAR-10 and SVHN, and the top-100 precision of CQ and PQ is even higher than that of SDH. This can be explained by the following fact: as metric distance approximators, the performances of PQ and CQ in semantic retrieval tasks are highly dependent on the quality of the underlying feature representations; and obviously, the CNN features are much better than the GIST descriptors. We further verify such explanations by computing the mAP based on the features’ Euclidean distances on the three datasets and obtained 0.1713, 0.1883, and 0.3519 on CIFAR-10, SVHN, and ImageNet respectively.

4.1.3 Comparing different discrete binary code solvers. Although the discrete hashing methods can learn high-quality hash codes, the optimization process can be computationally expensive. In
Table 4. Running time of the binary optimization solvers used in four discrete hashing methods under different settings. The results are in seconds. Column 2 to 4 show the running time of different code lengths with 50,000 training samples. Column 5 to 7 show the running time to generate 64 bits binary codes with different training sizes. The results of training 64-bit FastHash with 100000 samples are not shown because it couldn’t finish running in two hours and we therefore stopped it. The proposed LPMH is much faster than the best baselines, and it scales very well with long codes and large datasets.

<table>
<thead>
<tr>
<th>Method</th>
<th>Running Time@50000</th>
<th>Running Time@64 bits</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>16 bits</td>
<td>32 bits</td>
</tr>
<tr>
<td>FastHash</td>
<td>846.0</td>
<td>1710.1</td>
</tr>
<tr>
<td>COSDISH</td>
<td>2.6</td>
<td>10.6</td>
</tr>
<tr>
<td>SDH</td>
<td>6.5</td>
<td>6.9</td>
</tr>
<tr>
<td>LPMH</td>
<td>0.7</td>
<td>1.3</td>
</tr>
</tbody>
</table>

In order to test the scalability of the four most competitive discrete hashing methods (i.e. FastHash, COSDISH, SDH and LPMH), we profile the running time of the discrete optimization solvers used in those methods with different code lengths and training sizes. The results are shown in Table 4. Among the four discrete methods, FastHash is the slowest one. Specifically, we couldn’t finish running FastHash with 100,000 samples at 64 bits within 2 hours. The prohibitive complexity of FastHash is mainly due to its graph-cut based solution and pairwise losses (i.e. at least $O(n^2)$ complexity). Although COSDISH is also based on a pairwise objective, it adopts a smart column sampling algorithm to avoid dealing with the entire pairwise similarity matrix, thus achieving significant speed up. In comparison, the classification-based hashing methods are inherently easier to train, as demonstrated by the lower running time of SDH and LPMH, especially with larger training size. In particular, we find that the proposed LPMH solver scales very well with the increase of code length and training size. Actually, the running time of LPMH is much faster than the second fastest baseline (i.e. SDH), with up to 8x speed up across the tests, which demonstrates the superior efficiency and scalability of LPMH.

4.2 Cross-media Retrieval

4.2.1 Comparison with non-deep cross-media retrieval methods. The cross-media retrieval experiments are performed on the three widely used [27, 41, 52] multimedia datasets: Labelme, MIRFlickr and NUS-WIDE. We use 80% of the data in Labelme as the training set and database, and the remaining 20% are used as the query set. For MIRFlickr and NUS-WIDE, we randomly sample 2000 image-text pairs as the query set and the remaining data are used as the text and image databases. Additionally, we follow previous works [22, 52] to select 5000 image-text pairs from the database of MIRFlickr and NUS-WIDE as the training set to learn the multimedia hash functions. The learned hash functions are applied to both the database set and the query set to generate the database hash codes and query hash codes. Such practice has been widely adopted [3, 27, 41, 52] to test the out-of-sample extension capabilities of different cross-media hashing algorithms, and it also simulates realworld scenarios where labeled multimedia data is limited. Additionally, we follow [6, 32, 50] to set $R = 50$ while computing the mAP. In Labelme, the groundtruth neighbors of each query is defined as instances with the same class label. Since MIRFlickr and NUS-WIDE are multi-label datasets, two instances are defined to be similar if they share at least one common label.

We first compute the mAP of different methods by varying the hash codes from 16 bits to 64 bits, and the results are shown in Table 5. It can be noted from the table that the proposed LPMH
Table 5. The cross-modal retrieval mAP of the proposed LPMH and compared baselines on three multimodal datasets. The best result of each benchmark is shown in bold. The proposed LPMH outperforms the baselines in almost all the tests.

<table>
<thead>
<tr>
<th>Method</th>
<th>Labelme 16 bits</th>
<th>Labelme 32 bits</th>
<th>Labelme 64 bits</th>
<th>MIRFlickr 16 bits</th>
<th>MIRFlickr 32 bits</th>
<th>MIRFlickr 64 bits</th>
<th>NUS-WIDE 16 bits</th>
<th>NUS-WIDE 32 bits</th>
<th>NUS-WIDE 64 bits</th>
</tr>
</thead>
<tbody>
<tr>
<td>IMH</td>
<td>0.5295</td>
<td>0.4737</td>
<td>0.4251</td>
<td>0.6392</td>
<td>0.6384</td>
<td>0.6337</td>
<td>0.4950</td>
<td>0.4975</td>
<td>0.4885</td>
</tr>
<tr>
<td>CMFH</td>
<td>0.6881</td>
<td>0.7052</td>
<td>0.7217</td>
<td>0.6534</td>
<td>0.6508</td>
<td>0.6485</td>
<td>0.4960</td>
<td>0.4831</td>
<td>0.4824</td>
</tr>
<tr>
<td>LSSH</td>
<td>0.7486</td>
<td>0.7789</td>
<td>0.7884</td>
<td>0.6497</td>
<td>0.6749</td>
<td>0.6897</td>
<td>0.5013</td>
<td>0.5066</td>
<td>0.5299</td>
</tr>
<tr>
<td>CCQ</td>
<td>0.7798</td>
<td>0.7861</td>
<td>0.7849</td>
<td>0.6878</td>
<td>0.6940</td>
<td>0.7048</td>
<td>0.5126</td>
<td>0.5486</td>
<td>0.5450</td>
</tr>
<tr>
<td>SCM</td>
<td>0.6834</td>
<td>0.7900</td>
<td>0.8748</td>
<td>0.6692</td>
<td>0.6919</td>
<td>0.6970</td>
<td>0.5281</td>
<td>0.5553</td>
<td>0.5651</td>
</tr>
<tr>
<td>QCH</td>
<td>0.8222</td>
<td>0.8264</td>
<td>0.8279</td>
<td>0.6610</td>
<td>0.6994</td>
<td>0.7067</td>
<td>0.5562</td>
<td>0.5584</td>
<td>0.5565</td>
</tr>
<tr>
<td>SePH</td>
<td>0.8956</td>
<td>0.9031</td>
<td>0.9147</td>
<td>0.6965</td>
<td>0.7161</td>
<td>0.7407</td>
<td>0.5675</td>
<td>0.5963</td>
<td>0.6253</td>
</tr>
<tr>
<td>LPMH</td>
<td><strong>0.9256</strong></td>
<td><strong>0.9288</strong></td>
<td><strong>0.9298</strong></td>
<td><strong>0.7656</strong></td>
<td><strong>0.8128</strong></td>
<td><strong>0.8543</strong></td>
<td><strong>0.5955</strong></td>
<td><strong>0.6519</strong></td>
<td><strong>0.6637</strong></td>
</tr>
</tbody>
</table>

performs very well on both cross-media retrieval tasks, beating the compared methods in all three datasets. We observe that SePH has also shown strong performances in different tests, which is consistent with the results in previous work [27]. However, the performance of SePH is still secondary to the proposed LPMH, and the improvement of LPMH over SePH can be up to 15%; for instance, in the "text query image" task in MIRFlickr with 64-bit hash code. Note that SePH adopts a similar two-step hashing framework as the proposed LPMH, and therefore the better performance of LPMH can be attributed to the effectiveness of the proposed classification-based discrete optimization strategy. Another interesting observation is that the performances of different methods in "text query image" are typically slightly better than in "image query text". This can be explained by the fact that there usually exists a gap between feature representations and the semantic concept; and the semantic gap between the low-level image features and the concept are usually much larger than that between the texts and the concept. Similar findings have also been reported in [39, 41, 52].

The top-100 precision of different methods are reported in Table 6 and Figure 4. Specifically, Table 6 shows the top-100 precision with 64-bit hash code, while Figure 4 shows the precision with a varying number of hash bits. As can be noted from those results, the relative performances of different methods are generally consistent with the findings in the mAP tests, with the proposed LPMH leading in most of the computed metrics. Additionally, we have shown another view of the
Table 6. The test results of all the cross-media hashing algorithms in terms of top-100 precision on the three multimedia datasets. ‘T→I’ and ‘I→T’ refer to the results of “text query image” and “image query text” respectively. The ‘Mean’ column is the average results of ‘T→I’ and ‘I→T’. The hash code is set to 64 bits in this experiment. The proposed LPMH consistently outperforms the baselines in different datasets.

| Method | Labelme |  |  |  | Labelme |  |  |  | MIRFlickr |  |  |  | NUS-WIDE |  |  |  |  |  |  |  |  |  |  |  |
|--------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|
| T→I    | 0.2959  | 0.2674  | 0.2816  | Mean    | 0.2863  | 0.2674  | 0.2816  | Mean    | 0.2863  | 0.2674  | 0.2816  | 0.6046  | 0.5695  | 0.5871  | 0.4453  | 0.4379  | 0.4416  |
| I→T    | 0.5823  | 0.5070  | 0.5447  | Mean    | 0.5905  | 0.5108  | 0.5511  | Mean    | 0.5905  | 0.5108  | 0.5511  | 0.6119  | 0.6249  | 0.6184  | 0.4334  | 0.3525  | 0.3930  |
| IMH    | 0.7142  | 0.6844  | 0.6993  | Mean    | 0.6982  | 0.6813  | 0.6956  | Mean    | 0.6982  | 0.6813  | 0.6956  | 0.6456  | 0.6093  | 0.6275  | 0.4334  | 0.3525  | 0.3930  |
| LSSH   | 0.6375  | 0.4623  | 0.5499  | Mean    | 0.5317  | 0.4224  | 0.4842  | Mean    | 0.5317  | 0.4224  | 0.4842  | 0.6699  | 0.6359  | 0.6529  | 0.5036  | 0.4839  | 0.4974  |
| CCQ    | 0.8317  | 0.7349  | 0.7833  | Mean    | 0.7486  | 0.7089  | 0.7782  | Mean    | 0.7486  | 0.7089  | 0.7782  | 0.6705  | 0.6403  | 0.6554  | 0.5312  | 0.4142  | 0.4727  |
| SCM    | 0.7693  | 0.6803  | 0.7248  | Mean    | 0.7063  | 0.6529  | 0.6842  | Mean    | 0.7063  | 0.6529  | 0.6842  | 0.6816  | 0.6590  | 0.6703  | 0.5182  | 0.5144  | 0.5163  |
| QCH    | 0.8994  | 0.7950  | 0.8472  | Mean    | 0.8251  | 0.7688  | 0.8090  | Mean    | 0.8251  | 0.7688  | 0.8090  | 0.7227  | 0.6384  | 0.6806  | 0.5927  | 0.5431  | 0.5670  |
| SePH   | 0.8340  | 0.7301  | 0.7821  | Mean    | 0.7581  | 0.7043  | 0.7524  | Mean    | 0.7581  | 0.7043  | 0.7524  | 0.6705  | 0.6403  | 0.6554  | 0.5312  | 0.4142  | 0.4727  |
| LPMH   | 0.9286  | 0.8602  | 0.8944  | Mean    | 0.8638  | 0.8168  | 0.8504  | Mean    | 0.8638  | 0.8168  | 0.8504  | 0.8340  | 0.7301  | 0.7821  | 0.6705  | 0.6403  | 0.6554  |

Fig. 4. The top-100 precision of different cross-media hashing methods on three multimodal datasets. The length of the hash code is varied from 16 bits to 64 bits. The first row shows the “text query image” results and the second row shows the “image query text” results.
Fig. 5. The precision of different methods with varying number of returned neighbors. The hash code is set to 64 bits. The top row shows the results of “text query image” and the bottom row shows that of “image query text”.

Table 7. The training and test (encoding) time of different cross-media hashing methods on NUS-WIDE. We use 32-bit code in this experiment and the results are shown in seconds.

<table>
<thead>
<tr>
<th>Method</th>
<th>Time (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>IMH</td>
</tr>
<tr>
<td>Training</td>
<td>16.8</td>
</tr>
<tr>
<td>Test</td>
<td>0.4</td>
</tr>
</tbody>
</table>

We have also profiled the running time of different methods in Table 7. This experiment was performed on the NUS-WIDE dataset with 32-bit hash code. As can be seen from the table, the proposed method can be trained very fast, more than 10 times faster than the other competitive baselines such as SePH and QCH. In terms of test time, most of the compared methods are very fast, with SePH and LSSH being the two exceptions. The slow encoding of SePH and LSSH are caused by the high computational costs of non-linear transformation or matrix inverse operations. Although the boosted decision tree used in LPMH is also a nonlinear mapping, it only involves value comparisons and therefore could be much more computationally efficient. In order to factor both performance and costs into the comparison, we plot the mAP results against the training times in Figure 7. It can be noted that LPMH strikes the best balance between performance and training costs.
Fig. 6. The precision-recall curves of different methods using 64-bit hash codes. The first and second row show the results of “text query image” and “image query text” respectively. Better performance is indicated by larger area under the precision-recall curve. The proposed LPMH performs the best in this metric.

Fig. 7. The mAP performances of different cross-media hashing against the training time. The results are based on the experiment with 32-bit hash code on the NUS-WIDE dataset. The proposed method strikes the best balance between performance and training costs.

4.2.2 Comparison with deep learning. Deep cross-media hashing methods have claimed leading performances in a number of cross-media retrieval benchmarks recently. Therefore, we are interested to evaluate the proposed LPMH against the state-of-the-art deep cross-media hashing
Table 8. Comparing the proposed method with deep cross-media hashing methods on MIRFlickr and NUS-WIDE. CNN features are used for the proposed method. The results of the compared methods are directly obtained from [5]. The best performances are shown in bold, and the second best are underlined. Although the proposed LPMH is not based on deep learning, its performances are competitive against if not superior to the deep learning methods across our tests.

<table>
<thead>
<tr>
<th>Method</th>
<th>MIRFlickr</th>
<th>NUS-WIDE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Text query image</td>
<td>Image query text</td>
</tr>
<tr>
<td></td>
<td>16 bits</td>
<td>32 bits</td>
</tr>
<tr>
<td>MMNN [33]</td>
<td>0.6815</td>
<td>0.6992</td>
</tr>
<tr>
<td>CHN [4]</td>
<td>0.7631</td>
<td>0.7814</td>
</tr>
<tr>
<td>CDQ [5]</td>
<td>0.8477</td>
<td>0.8495</td>
</tr>
<tr>
<td>LPMH</td>
<td><strong>0.8658</strong></td>
<td><strong>0.9030</strong></td>
</tr>
</tbody>
</table>

Table 9. Performances of the proposed method with and without the bit balance constraints on the CIFAR-10 and NUS-WIDE datasets, where 'I→I', 'I→T' and 'T→I' represent “image query image”, “text query image” and “image query text” respectively. Better results can be obtained for both single-media retrieval and cross-media retrieval tasks when the bit balance constraint is enabled.

<table>
<thead>
<tr>
<th>Balance Constraints</th>
<th>CIFAR-10 (I→I)</th>
<th>NUS-WIDE (T→I)</th>
<th>NUS-WIDE (I→T)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>16 bits</td>
<td>32 bits</td>
<td>64 bits</td>
</tr>
<tr>
<td>No</td>
<td>0.6457</td>
<td>0.6992</td>
<td>0.7251</td>
</tr>
<tr>
<td>Yes</td>
<td><strong>0.6616</strong></td>
<td><strong>0.7053</strong></td>
<td><strong>0.7281</strong></td>
</tr>
</tbody>
</table>

methods, including MMNN [33], CHN [4] and CDQ [5]. In order for a fair comparison, we use AlexNet [17] to extract the fc7-layer CNN features for the proposed method, and strictly follow the same training and evaluation settings in [5]. The results of this experiment are shown in Table 8. We observe that LPMH achieves better performances than all the compared deep methods on MIRFlickr, and it is secondary to only CDQ in NUS-WIDE. Note that the small performance gap in NUS-WIDE is due to the fact that CDQ is trained with an end-to-end hashing framework, while the proposed method only uses CNN features and have not exploited the full potential of deep neural networks. Overall, the competitive performances against state-of-the-art deep learning algorithms further consolidate the effectiveness of the proposed multimedia hashing method.

4.3 Evaluation of Bit Balance Constraint

We have studied the effect of the widely used bit balance constraints on the proposed method, and this experiment was carried out on the CIFAR-10 and NUS-WIDE dataset. The performance results of the proposed method with and without the bit balance constraint are shown in Table 9. It can be observed that the bit balance constraint has a positive impact on the quality of the learned binary codes, and better results can be obtained when the constraint is incorporated. We remark that the ability to incorporate bit balance constraints into the binary code learning is one of the advantages over existing discrete hashing methods [25, 29, 36].
Learning Label Preserving Binary Codes for Multimedia Retrieval

4.4 Study of Different Loss Functions

The proposed hashing method is able to accommodate different types of loss functions in a unified discrete optimization framework. Here we evaluate the performance of the proposed method using four different types of loss functions, namely, the cross-entropy loss, squared loss, logistic loss and hinge loss. Those loss functions have been briefly introduced in Section 3.2. We perform this experiment on CIFAR-10 and NUS-WIDE, and the results are shown in Figure 8. Interestingly, we find that while different loss functions could be advantageous in different scenarios, the performance results of different loss functions are very close in most tests, which demonstrates the robustness and consistency of the proposed optimization method with a range of different loss types. In general, the ability to incorporate different loss functions in a unified optimization framework greatly extends the flexibility of LPMH.

5 CONCLUSION

In this paper, we propose a novel multimedia hashing method, referred to as Label Preserving Multimedia Hashing (LPMH), for large-scale multimedia similarity search. Specifically, we exploit a two-stage discrete hashing framework and propose a general approach for solving binary codes through classification-based optimization objectives. The proposed discrete optimization method is both flexible and efficient: it can accommodate different types of loss functions with minimal changes to the learning steps; it can also be easily combined with the bit balance constraint to obtain highly compact and discriminative binary codes in a much faster speed than existing methods. Additionally, the high-quality binary codes are further incorporated within a boosted ensemble learning pipeline to obtain the media-specific hash functions for effective out-of-sample extensions. We have conducted extensive experiments on widely used large-scale datasets and compared with a range of state-of-the-arts in both single-media hashing and cross-media hashing research. The experimental results demonstrate the efficiency and effectiveness of LPMH in generating highly discriminative compact hash codes for multimedia retrieval tasks.

ACKNOWLEDGMENTS

This material is based upon work partially supported by NASA under Grant Number NNX15AV40A. Any opinions, findings, and conclusions or recommendations expressed in these materials are those of the authors and do not necessarily reflect the views of NASA.
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