Adaptive Asymmetric Label-guided Hashing for Multimedia Search

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Abstract

With the rapid growth of multimodal media data on the Web in recent years, hash learning methods as a way to achieve efficient and flexible cross-modal retrieval of massive multimedia data have received a lot of attention from the current Web resource retrieval research community. Existing supervised hashing methods simply transform label information into pairwise similarity information to guide hash learning, leading to a potential risk of semantic error in the face of multi-label data. In addition, most existing hash optimization methods solve NP-hard optimization problems by employing approximate approximation strategies based on relaxation strategies, leading to a large quantization error. In order to address above obstacles, we present a simple yet efficient Adaptive Asymmetric Label-guided Hashing, named A2LH, for Multimedia Search. Specifically, A2LH is a two-step hashing method. In the first step, we design an association representation model between the different modality representations and semantic label representation separately, and use the semantic label representation as an intermediate bridge to solve the semantic gap existing between different modalities. In addition, we present an efficient discrete optimization algorithm for solving the quantization error problem caused by relaxation-based optimization algorithms. In the second step, we leverage the generated hash codes to learn the hash mapping functions. The experimental results show that our proposed method achieves optimal performance on all compared baseline methods.

I. Introduction

Since entering the era of big data, mobile Internet and IoT platforms generate huge amount of multimodal data, such as video, audio, text, images, etc., every day. However, it is very difficult to retrieve the information of interest to users quickly from it. One is due to the huge scale of data, large data dimension and complex data structure, which leads to the inability of effective storage and analysis; second, the problem of "heterogeneous gaps" between different modalities due to the wide variety of data types and modalities, and the "semantic gaps" between low-order features and high-order semantics, which makes it difficult to correlate them. Therefore, how to establish effective large-scale, multi-modal, multi-granularity, multi-scale data efficient indexing mechanism to achieve efficient storage and search of massive and complex data has become a highly hot issue in industry and academia.

Nearest Neighbor Search (NNS) is a classical data search technique in the field of information retrieval, which aims to accurately retrieve the nearest/most similar sample to the query sample in the database and is widely used in many fields such as data mining, video analysis, and information retrieval. However, nearest neighbor search retrieval is difficult to be accepted in massive data due to its high time consumption. Therefore, Approximate Nearest Neighbor Search (ANNS) meets the retrieval needs of massive data in practical applications by finding potentially similar and not-exactly-similar samples and significantly improving the retrieval efficiency by sacrificing partial precision. It can effectively replace the nearest neighbor search technique by balancing the retrieval accuracy and efficiency. Hashing, as a branch of ANNS, uses hardware-friendly exclusive OR (XOR) instead of traditional matrix computation for efficient Hamming distance metrics during retrieval by mapping high-dimensional data features into a low-dimensional binary space with guaranteed consistent data similarity through a hash function.

However, in the large-scale multimodal data environment, the single-modal data retrieval capability can

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no longer meet the demand for information retrieval functions, and cross-modal retrieval between different modalities is needed. Although the feature expressions and presentations may be completely different between different modalities, there exists semantic consistency, because when a person views a photo, it is easy to correspond the text that is consistent with the photo description to it and vice versa. Cross-modal retrieval means that given a retrieval sample of one modality, another modality data sample with semantic similarity is returned, such as text search for image, image search for text, etc. Therefore, hash learning methods for large-scale multimodal data retrieval have become a new hot research problem, whose core idea is to map different modalities into a unified Hamming space, solve the "heterogeneous gap" problem between different modalities, and achieve efficient cross-modal retrieval.

The evolution of hash learning can be broadly outlined in two ways: data-independent hashing and data-dependent hashing. **Data-independent hashing**, as the name implies, mapping hash (hash function) is independent of the data and is obtained independently of the data. In other words, the generation process of hash functions is based on manual design or random mapping approach. Representative works are Locality-Sensitive Hashing (LSH) and its variant models. Since the generation of the hash function is not directly related to the data itself, it requires the participation of experts in the relevant fields to generate better quality hash codes, for example, to do medical image data retrieval requires the participation of relevant imaging physicians, because it requires professional physicians to guide the processing rules of the hash function on the relevant domain data, and requires longer hash code bits to obtain more satisfactory retrieval results (usually longer than 1024 bits). This type of hash learning method cannot be widely used in practical applications because of the limitation of the professional field and the long hash code bits. **Data-dependent hashing**, which is the opposite of data-independent hash learning, has gradually become mainstream with the development of the field of data mining and pattern recognition based on data-dependent hashing techniques. Learning potential knowledge from data improves the discriminative power of the hash function and enhances the semantics of the generated hash code, which makes it possible to obtain high retrieval performance even for short-bit hash codes (usually shorter than 128 bits) and has received

wide attention from academia and industry.

Data-dependent hashing requires learning the relevant mapping functions (hash functions) through the potential knowledge and feature distributions embedded in the data, so it is also known as learning to hashing (L2H), which can be roughly classified into two categories: unsupervised and supervised hashing. Unsupervised hashing usually generates hash codes by mining the data itself for potential correlations or inter-modal feature similarities without label supervision. In contrast, supervised hash learning generically possesses better retrieval performance than unsupervised hashing due to the involvement of semantic labels. Most existing supervised hash learning methods are based on a one-step learning strategy, in other words, hash codes and hash functions are learned and optimized through a unified objective function, which inevitably has several drawbacks: (1) increasing the complexity of optimizing and solving the objective function, resulting in the inability to obtain the optimal solution; (2) the inability to flexibly change the hash mapping function, because using a new hash mapping function will result in retraining the entire objective function. In addition, most hash learning methods leverage the relaxation-based optimization strategies to solve the NP-hard problem posed by discrete hash codes, leading to a large quantization error that affect the retrieval performance of the generated hash codes. In addition to the above limitations, there are still a important issue that need to be addressed, i.e., The semantic gap between differentmodalities is not well bridged.

In order to address the above limitations, we present a two-step **A**daptive **A**symmetric **L**abel-guided **H**ashing (**A2LH**). Specifically, in the first step, we construct a multi-label common semantic space and use this space as a bridge to bridge the semantic gap that exists between different modalities. At the same time, in order to explore the complex nonlinear relationships within different modalities, we use kernelization operations to improve the characterization ability of different modalities. In addition, in the optimization phase, we use discrete optimization strategies to solve the quantization error problem caused by the relaxation strategy. As a result, the semantic and discriminative power of hash codes will be substantially enhanced. In the second step, we use the hash codes generated in the first stage to guide the learning of the hash mapping function.

The main contributions of the paper can be summa-

rized as follows:

1. An adaptive asymmetric hash learning framework with a common multi-semantic space as a bridge is proposed to establish the association between different modalities and the semantic space, so as to effectively bridge the heterogeneous gap existing between different modalities and improve the discriminative power of the generated hash codes.

2. A discrete optimization strategy based on the augmented Lagrangian method is proposed to solve the quantization error caused by the relaxation strategy and improve the discriminative power of the generated hash codes.

3. The experimental results show that our proposed method achieves optimal performance on two publicly available datasets.

The paper is organized as follows, in Section II, we briefly review the work closely related to this paper. Section III describes our model in detail. Section IV gives the results of the experiments, and Section V concludes the work.

II. RELATED WORKS

The existing hash learning functions can be broadly classified according to the learning paradigm into unimodal hash and cross-modal hash [42]. Unimodal hashing considers only a single modality (e.g., image, text, audio, or video) in the retrieval query and model training phases by maintaining similarity information in the Hamming space of a single modality, which often applied to visual search or text search tasks. In cross-modal hash retrieval, the query is a single modality and the training process consists of multi-modal modalities, which is mainly applied to large-scale media data retrieval, such as text retrieval image or image retrieval text tasks.

i. Unimodal Hashing

Early works on hash learning focused on unimodal retrieval field [33, 24, 53, 15, 58, 55, 56, 28]. For example, SH [9] proposes a new hypersphere based hash function that maps more spatially coherent data points into binary codes. Representative works include FSDH [8] embeds the semantic information of different classes of

tags on the corresponding hash codes by regression strategy. CSQ [57] accommodates new image representations by constructing a flexible indexing structure independent of any image descriptor training set. OEH [22] computes the given order relationship embedded between data points in order to learn the binary code that preserves the ranking. SDAH [49] proposes an asymmetric learning framework with different dimensions to generate high-quality image hash codes by considering the information capacity problem of image representation and deep label embedding. FISH [3] consists of two modules, where the spatial filtering module is responsible for solving the fine-grained feature extraction and the feature filtering module is responsible for solving the feature refinement problem. SCRATCH [2] finds a potential semantic space using collective matrix decomposition of kernelized features and semantic embedding labels to maintain intra- and inter-modal similarity. DLTH [16] captures the relative similarity of the new triplets by introducing more triplets and a new listed triplet loss. CUDH [7] recursively learns discriminative clustering through a soft clustering model and generates binary codes with high similarity responses. EDDH [50] generates robust hash codes by considering the visual relationships between image pairs while combining semantic labeling information to generate a fine-grained visual-semantic pair similarity matrix.

ii. Cross-modal Hashing

Cross-modal hash learning is mainly to achieve efficient retrieval between different modalities, such as text retrieve images or image retrieves text. Cross-modal hashing can be broadly classified according to the learning paradigm: unsupervised cross-modal hashing and supervised cross-modal hashing.

ii.1 Unsupervised Cross-modal Hashing

Unsupervised hashing accomplishes the generation of hash codes by mining inter- and intra-modal correlations of different modalities without the assistance of label semantics [11, 44, 14, 52, 30]. Representative works include MGCMH [47] integrates multigraph learning and hash function learning into a joint framework using an unsupervised learning paradigm to uniformly map data from different modalities into the same hash space. UDCMH [46] is a model based on deep learn-

ing and matrix decomposition with binary latent factor fusion for multimodal data hash code generation in a self-learning manner. DJSRH [38] learns the original neighborhood information of different modalities by constructing a joint semantic affinity matrix, while the proposed reconstruction framework maximally reconstructs the above joint semantic relations to generate robust hash codes. UCH [13] proposes a novel unsupervised biorthogonal network in which the outer-loop network learns uniform representations of different modalities and the inner-loop network generates hash codes. JDSH [23] proposes a novel unsupervised cross-modal joint learning model by constructing joint modal similarity matrices to fully preserve cross-modal semantic associations between instances and distribution-based similarity decision and weighting (DSDW) sampling and weighting schemes in order to generate robust hash codes. DCSH [10] is a two-step unsupervised cross-modal hash learning method that decouples the optimization into two parts: binary optimization and hash function learning. CLIP4Hashing [59] employs a CLIP model to construct a hash learning framework, which is utilized to solve the problem of heterogeneous divide between different modalities in Hamming space.

ii.2 Supervised Cross-modal Hashing

Compared to unsupervised cross-modal hashing, supervised cross-modal hashing using label information can significantly increase the semantics of hash codes and thus improve the retrieval performance of hash codes [6, 29, 41, 19, 12, 17, 35]. Representative works include LBMCH [45] describes the semantic correspondence across schemas by bridging the gaps that exist in different hash spaces. RCMH [31] is a three-step hash learning model in which, in one step, each training image is assigned a hash code based on the hyperplane learned in the previous iteration; in the second step, the binary bits are smoothed by a graph-regularized representation so that similar data points have similar bits; and in the third step, a set of binary classifiers are trained to predict the regularized bits with maximum residual. SMFH [20] is a supervised cross-modal hash learning method, which solves the multimodal hash learning problem by decomposing the collective non-negative matrix of different modalities. CMFH [39] is a cross-modal hash learning method based on collective matrix decomposition, which considers both the label

consistency of different modalities and the local geometric consistency of each modality. NRDH [48] reconstructs the raw information of different modes by a deep nonlinear descriptor of the common latent representations in reverse, while combining it with a hash learning framework to generate robust hash codes. DDASH [32] is an asymmetric hash learning method, which learns the hash codes of database instances by matrix decomposition strategy and the hash codes of query instances by using deep hash function. This not only can take full advantage of the information of large-scale data, but also can reduce the training time of the model. NSDH [51] proposes an asymmetric nonlinear hash learning framework that can incrementally mine the deep semantic information of different modalities layer by layer to generate high-quality hash codes. CMCH [1] generates discriminative hash codes by progressively mining the structural consensus and informative transformation semantics of different modalities. SASH [36] mines the relevance of semantic labels by maintaining the consistency of feature and label spaces and uses this relevance to optimize the similarity matrix. Although the above cross-modal supervised methods achieve good retrieval performance, they neglect to fully exploit the potential uniform geometric structure representation of different modalities and the consideration of semantic information completeness issues, resulting in degraded retrieval performance. Therefore, in this paper, we improve the retrieval performance of hash codes by mining the potential uniform integrity representation information of different modalities.

III. Our proposed **A2LH**

i. Notation

Let $\mathbb{I} = \{i_i\}_{i=1}^n$ be the dataset with n instances, and $i_i = \{\mathbf{X}_i^{(m)}\}_{m=1}^M$, m is the m-th modality. For convenience, in this paper we will only consider data from two modalities, i.e., visual modality and text modality. $\mathbf{L} \in \mathbb{R}^{c \times n}$ is the semantic information, c is the number of categories. In this paper, we denote $\mathbf{X}^1$ and $\mathbf{X}^2$ are visual modality and text modality, respectively. $\mathbf{B} \in \mathbb{R}^{k \times n}$ is the hash codes, k is the length of hash codes. The notations used in **A2LH** are listed in Table. 1.

Table 1: *Notations.*

Notation	Explanations
$\mathbf{X}^{(m)} \in \mathbb{R}^{d_m \times n}$	The m-th modality representation
$\phi(\mathbf{X}^{(m)}) \in \mathbb{R}^{q \times n}$	The m-th modality kernelized representation
$\mathbf{V}^{(m)} \in \mathbb{R}^{q \times q}$	The m-th modality-specific space
$\mathbf{U} \in \mathbb{R}^{q \times n}$	The common space
$\mathbf{B} \in \mathbb{R}^{k \times n}$	The learned hash codes
$\mathbf{R} \in \mathbb{R}^{k \times c}$	Linear projection
$\mathbf{S} \in \mathbb{R}^{n \times n}$	Similarity matrix
$\mathbf{C} \in \mathbb{R}^{k \times q}$	Linear mapping matrix
$\mathbf{L} \in \mathbb{R}^{c \times n}$	Semantic labels
$\mathbf{W}^{(m)} \in \mathbb{R}^{k \times q}$	The m-th modality hash function
n	Number of instances
k	Length of hash codes
c	Number of categories

ii. The first step of **A2LH**

ii.1 Kernelization

The kernelization technique is one of the techniques often used in the field of pattern recognition to mine the non-linear complex key within the data. Therefore, to better capture the potential nonlinear relationships between different modalities, the paper uses an expression based on RBF kernel mapping. Specifically, the RBF kernel mapping-based expression makes the kernelized features more discriminative by mining the nonlinear relationships among data, and for a sample x_i, its kernelized feature $\phi(x_i)$ can be expressed as,

$$\phi(x_i) = \left[\exp(\frac{-||x_i - a_1||_2^2}{2\rho^2}), ..., \exp(\frac{-||x_i - a_q||_2^2}{2\rho^2}) \right]^\top, \tag{1}$$

where a_q represents the randomly selected q anchor instances and ρ is the width.

ii.2 Modality-Specific Association Learning

The different modalities describe the same common space from different perspectives, then these modalities should exist in the common space $\mathbf{U} \in \mathbb{R}^{q \times n}$. In addition, the different modalities also have their specific feature space, i.e. modality-specific space $\mathbf{V}_m \in \mathbb{R}^{q \times q}$.

Then, we obtain,

$$\min_{\mathbf{U}, \mathbf{V}_m} \mu_m ||\phi(\mathbf{X}^{(m)}) - \mathbf{V}_m \mathbf{U}||_F^2$$
$$s.t. \ \mathbf{V}_m^\top \mathbf{V}_m = \mathbf{I}_q, \sum_m \mu_m = 1, \mu_m > 0, \tag{2}$$

where μ_m is a weight parameter for the m-th modality. In the most existing hashing methods, the weight parameter μ_m is fixed. However, the degree of contribution of different modalities to the common latent representation is different, and manual adjustment of the parameters firstly cannot accurately determine the degree of contribution of different modalities, i.e., the optimal values of μ_m. Secondly, searching for the optimal parameters leads to huge time consumption and cannot be applied in practical scenarios. Therefore, in this paper, we propose an **adaptive** learning scheme to obtain the values of μ_m. In order to avoid "winner-take-all" phenomenon, we introduce a exponential parameter ζ to smooth the contribution of different modalities, we obtain,

$$\min_{\mu_m, \mathbf{U}, \mathbf{V}_m} \mu_m^\zeta ||\phi(\mathbf{X}^{(m)}) - \mathbf{V}_m \mathbf{U}||_F^2$$
$$s.t. \ \mathbf{V}_m^\top \mathbf{V}_m = \mathbf{I}_q, \sum_m \mu_m = 1, \mu_m > 0, \tag{3}$$

where $\zeta \geq 2$. In this way, we can learn the optimal weighting parameters. In addition, we associate the common space $\mathbf{U}$ with the hash space $\mathbf{B}$ by the use of the linear mapping $\mathbf{C} \in \mathbb{R}^{k \times q}$. The formula is,

$$\min_{\mathbf{U}, \mathbf{C}, \mathbf{B}} ||\mathbf{B} - \mathbf{C}\mathbf{U}||_F^2. \tag{4}$$

ii.3 Multi-Semantic Space Learning

The core problem of cross-modal retrieval is to solve the problem of heterogeneous gap existing between different modalities. We address this problem from another perspective, i.e., (i) constructing a reasonable common space; (ii) then associating the different modalities with it. This strategy has the following advantages: (1) it bridges the heterogeneity gap among different modalities; (2) it can be easily extended to multiple modalities. Moreover, the problem of semantically accurate representation of multi-label needs to be addressed, because constructing the multi-label pair similarity matrix directly leads to semantic errors. For example, there are three samples x_1, x_2, x_3, corresponding to labels $y_1 = [0, 1, 1, 1, 1, 1, 1], y_2 = [0, 1, 1, 1, 1, 1, 1], y_3 = [1, 1, 0, 0, 0, 0, 0]$, and the reconstructed pair-wise similarity information is $S_{12} = S_{23} = S_{13} = 1$. However, the distance between x_1 and x_2 is smaller than the distance between x_1 and x_3. In the above development, we leverage a linear projection $\mathbf{R} \in \mathbb{R}^{k \times c}$ to embed the multi-label vectors to a final common space, i.e., the Hamming space $\mathbf{B}$. In general, associating label semantic information to each category increases the semantics of the learned hash codes,

$$\min_{\mathbf{B}, \mathbf{R}} ||\mathbf{RL} - \mathbf{B}||_F^2$$
$$s.t. \ \mathbf{B} \in \{-1, 1\}^{k \times n}. \quad (5)$$

ii.4 Hash Code Learning

The KSH Method is a very well-known hash learning method that proposes a semantic preservation principle based on hash code learning, as

$$\min_{\mathbf{B}} ||\mathbf{B}^\top \mathbf{B} - k\mathbf{S}||_F^2$$
$$s.t. \ \mathbf{B} \in \{-1, 1\}^{k \times n}. \quad (6)$$

However, Equation (6) has several drawbacks: (i) how to construct the $n \times n$ pairwise similarity matrix $\mathbf{S}$ efficiently; (ii) how to solve the discrete optimization efficiently. In response to the drawback (i), we replace $\mathbf{S}$ with $2\mathbf{L}^\top \mathbf{L} - \mathbf{11}^\top$, where $\mathbf{1}$ means a vector with all elements being one, then the time cost $\mathcal{O}(n^2)$ can be reduced to $\mathcal{O}(n)$. For the drawback (ii), we construct learning-efficient and efficient asymmetric hash learning architectures, and a large number of researchers have shown that the use of asymmetric hash learning

frameworks significantly outperforms symmetric hash learning frameworks in terms of both learning efficiency and retrieval accuracy. Combining the Eq. (4), we substitute one of $\mathbf{B}$ in Eq. (4) with multi-modal matrix $\mathbf{CU}$ to construct an asymmetric learning framework, as

$$\min_{\mathbf{C}, \mathbf{B}, \mathbf{U}} ||\mathbf{B}^\top \mathbf{CU} - k\mathbf{S}||_F^2 + \alpha ||\mathbf{B} - \mathbf{CU}||_F^2$$
$$s.t. \ \mathbf{B} \in \{-1, 1\}^{k \times n}, \quad (7)$$

where α is a trade-off parameter. In order to enhance the semantic information of the learned hash codes, the second $\mathbf{B}$ in Eq. (4) also needs to be replaced with Eq. (5), then we obtain,

$$\min_{\mathbf{R}, \mathbf{C}, \mathbf{B}, \mathbf{U}} ||(\mathbf{RL})^\top \mathbf{CU} - k\mathbf{S}||_F^2 + \alpha ||\mathbf{B} - \mathbf{CU}||_F^2 + \beta ||\mathbf{RL} - \mathbf{B}||_F^2$$
$$s.t. \ \mathbf{B} \in \{-1, 1\}^{k \times n}, \quad (8)$$

where β is a balance parameter.

iii. Optimization

Combing Eq. (8) and Eq. (2), we obtain the overall objective function,

$$\min_{\mu_m, \mathbf{R}, \mathbf{C}, \mathbf{B}, \mathbf{U}, \mathbf{V}_m} ||(\mathbf{RL})^\top \mathbf{CU} - k\mathbf{S}||_F^2 + \alpha ||\mathbf{B} - \mathbf{CU}||_F^2$$
$$+ \beta ||\mathbf{RL} - \mathbf{B}||_F^2 + \mu_m{}^\zeta ||\phi(\mathbf{X}^{(m)}) - \mathbf{V}_m \mathbf{U}||_F^2 + \eta \mathcal{R}(\mathbf{RL}, \mathbf{U})$$
$$s.t. \ \mathbf{B} \in \{-1, 1\}^{k \times n}, \ \mathbf{V}_m{}^\top \mathbf{V}_m = \mathbf{I}_q, \sum_m \mu_m = 1, \mu_m > 0, \quad (9)$$

where η is a regularization parameter, the term $\mathcal{R}(\mathbf{R}, \mathbf{U}) = ||\mathbf{RL}||_F^2 + ||\mathbf{U}||_F^2$ is a regularization term that avoids overfitting.

Solving Eq. (9) is actually an NP-Hard problem due to the discrete value optimization. Many methods are optimized by a two-step approach, i.e., first making an approximation to the discrete values and then solving for the approximation; In the second step, the approximation variables are processed using the *sgn* function. Such an approach solves the NP-hard problem brought by the discretized value solution, but it also causes a large amount of quantization error, which affects the retrieval performance. Some methods use the DDC solving strategy to solve hash codes bit-by-bit. Although this method solves the quantization loss brought by the relaxation strategy, it takes k iterations to optimize a hash code of length k bits, which leads to a large amount of time consumption.

In this paper, we use a discrete optimization strategy to generate discrete hash codes directly in one step to solve the problems of quantization error and excessive time consumption. Specifically, we fix the other variables by solving for one of them. The overall optimization process of Eq. (9) is as follows,

μ_m**-step**: We fix the the other variables, i.e., $\mathbf{R}, \mathbf{C}, \mathbf{B}, \mathbf{U}, \mathbf{V}_m$, the updating for variable μ can be reformulated as,

$$\min_{\mu_m} \mu_m{}^\zeta ||\phi(\mathbf{X}^{(m)}) - \mathbf{V}_m\mathbf{U}||_F^2 \quad \sum_m \mu_m = 1, \mu_m > 0. \quad (10)$$

We leverage the Lagrangian multiplier algorithm to reduce the difficulty of solving the variable μ_m, thus the Eq. (10) can be reformulated as,

$$\min_{\mu_m} \mu_m{}^\zeta ||\phi(\mathbf{X}^{(m)}) - \mathbf{V}_m\mathbf{U}||_F^2 - \Xi(\mathbf{1}^\top\mu - 1), \quad (11)$$

where $\mu = [\mu_1, \mu_2, ..., \mu_M]^\top \in \mathbb{R}^M$ is the vector of weights for the different modalities.

Setting the derivative with respect to Ξ and μ to zero, the solution of the variable μ_m can be written as,

$$\mu_m = \frac{\Delta_m^{1/1-\zeta}}{\sum_{m=1}^M \Delta_m^{1/1-\zeta}}, \quad (12)$$

where $\Delta_m = ||\phi(\mathbf{X}^{(m)}) - \mathbf{V}_m\mathbf{U}||_F^2$.

R-step: We fix the the other variables, i.e., $\mu_m, \mathbf{C}, \mathbf{B}, \mathbf{U}, \mathbf{V}_m$, the updating for variable $\mathbf{R}$ can be reformulated as

$$\min_{\mathbf{R}} ||(\mathbf{RL})^\top\mathbf{CU} - k\mathbf{S}||_F^2 + \beta||\mathbf{RL} - \mathbf{B}||_F^2 + \eta\mathcal{R}(\mathbf{RL}). \quad (13)$$

Then, Eq. (13) can be rewritten as,

$$\min_{\mathbf{R}} tr(\mathbf{L}^\top\mathbf{R}^\top\mathbf{CUU}^\top\mathbf{C}^\top\mathbf{RL} - 2k\mathbf{L}^\top\mathbf{R}^\top\mathbf{CUS}^\top \\ + \beta\mathbf{RLL}^\top\mathbf{R}^\top - 2\beta\mathbf{BL}^\top\mathbf{R}^\top + \eta\mathbf{RLL}^\top\mathbf{R}^\top). \quad (14)$$

We compute the deviation w.r.t $\mathbf{R}$ to 0. Then, we obtain the closed-form solution as,

$$\mathbf{R} = (\mathbf{CUU}^\top\mathbf{C}^\top + (\beta + \eta)\mathbf{I})^{-1}(k\mathbf{CUS}^\top\mathbf{L}^\top + \beta\mathbf{BL}^\top)(\mathbf{LL}^\top)^{-1} \quad (15)$$

Then, the term $k\mathbf{CUS}^\top\mathbf{L}^\top$ can be obtained by $2(\mathbf{CUL}^\top)(\mathbf{LL}^\top)^\top - (\mathbf{CU1})(\mathbf{L1})^\top$. which consumes $\mathcal{O}(n)$.

C-step: We fix the the other variables, i.e., $\mu_m, \mathbf{R}, \mathbf{B}, \mathbf{U}, \mathbf{V}_m$, the updating for variable $\mathbf{C}$ can be reformulated as,

$$\min_{\mathbf{C}} ||(\mathbf{RL})^\top\mathbf{CU} - k\mathbf{S}||_F^2 + \alpha||\mathbf{B} - \mathbf{CU}||_F^2. \quad (16)$$

Then, Eq. (16) can be rewritten as,

$$\min_{\mathbf{C}} tr(\mathbf{L}^\top\mathbf{R}^\top\mathbf{CUU}^\top\mathbf{C}^\top\mathbf{RL} - 2k\mathbf{SU}^\top\mathbf{C}^\top\mathbf{RL} \\ - 2\alpha\mathbf{BU}^\top\mathbf{C}^\top + \alpha\mathbf{CUU}^\top\mathbf{C}^\top). \quad (17)$$

We compute the deviation w.r.t $\mathbf{C}$ to 0. Then, we obtain the closed-form solution as,

$$\mathbf{C} = (\mathbf{RLL}^\top\mathbf{R}^\top + \alpha\mathbf{I})^{-1}(k\mathbf{RLSU}^\top + \alpha\mathbf{BU}^\top)(\mathbf{UU}^\top)^{-1} \quad (18)$$

Similar, the term $\mathbf{RLSU}^\top$ can be rewritten as $2(\mathbf{RLL}^\top)(\mathbf{UL}^\top)^\top - (\mathbf{RL1})(\mathbf{U1})^\top$, which consumes $\mathcal{O}(n)$.

B-step: We fix the the other variables, i.e., $\mu_m, \mathbf{R}, \mathbf{C}, \mathbf{U}, \mathbf{V}_m$, the updating for variable $\mathbf{B}$ can be reformulated as,

$$\min_{\mathbf{B}} \alpha||\mathbf{B} - \mathbf{CU}||_F^2 + \beta||\mathbf{RL} - \mathbf{B}||_F^2 \\ s.t. \ \mathbf{B} \in \{-1, 1\}^{k \times n}. \quad (19)$$

Then, Eq. (19) can be rewritten as,

$$\min_{\mathbf{B}} tr((\alpha + \beta)\mathbf{BB}^\top - 2\alpha\mathbf{CUB}^\top - 2\beta\mathbf{RLB}^\top). \quad (20)$$

Note that, the term $\mathbf{BB}^\top = nk$ is a constant. Therefore, Eq. (21) can be reformulated as,

$$\max_{\mathbf{B}} tr((\alpha\mathbf{CU} + \beta\mathbf{RL})\mathbf{B}^\top). \quad (21)$$

The closed-form solution of the variable $\mathbf{B}$ is,

$$\mathbf{B} = \alpha\mathbf{CU} + \beta\mathbf{RL}. \quad (22)$$

U-step: We fix the the other variables, i.e., $\mu_m, \mathbf{R}, \mathbf{C}, \mathbf{B}, \mathbf{V}_m$, the updating for variable $\mathbf{U}$ can be reformulated as,

$$\min_{\mathbf{U}} ||(\mathbf{RL})^\top\mathbf{CU} - k\mathbf{S}||_F^2 + \alpha||\mathbf{B} - \mathbf{CU}||_F^2 \\ + \mu_m{}^\zeta ||\phi(\mathbf{X}^{(m)}) - \mathbf{V}_m\mathbf{U}||_F^2 + \eta\mathcal{R}(\mathbf{U}), \quad (23)$$

Then, Eq. (23) can be rewritten as,

$$\min_{\mathbf{U}} tr(\mathbf{L}^\top\mathbf{R}^\top\mathbf{CUU}^\top\mathbf{C}^\top\mathbf{RL} - 2k\mathbf{SU}^\top\mathbf{C}^\top\mathbf{RL} \\ + \alpha\mathbf{CUU}^\top\mathbf{C}^\top - 2\alpha\mathbf{BU}^\top\mathbf{C}^\top - 2\mu_m{}^\zeta\phi(\mathbf{X}^{(m)})\mathbf{U}^\top\mathbf{V}_m{}^\top \\ + \mu_m{}^\zeta\mathbf{V}_m\mathbf{UU}^\top\mathbf{V}_m{}^\top + \eta\mathbf{UU}^\top). \quad (24)$$

The closed-form solution of the variable $\mathbf{U}$ is,

$$\mathbf{U} = (\mathbf{C}^\top \mathbf{R} \mathbf{L} \mathbf{L}^\top \mathbf{R}^\top \mathbf{C} + \alpha \mathbf{C}^\top \mathbf{C} + \mu_m{}^\zeta \mathbf{V}_m{}^\top \mathbf{V}_m + \eta \mathbf{I})^{-1}$$
$$\cdot (k \mathbf{C}^\top \mathbf{R} \mathbf{L} \mathbf{S} + \alpha \mathbf{C}^\top \mathbf{B} + \mu_m{}^\zeta \mathbf{V}_m{}^\top \phi(\mathbf{X}^{(m)})) \tag{25}$$

$\mathbf{V}_m$-**step**: We fix the the other variables, i.e., $\mu_m, \mathbf{R}, \mathbf{C}, \mathbf{B}, \mathbf{U}$, the updating for variable $\mathbf{V}_m$ can be reformulated as,

$$\min_{\mathbf{V}_m} \mu_m{}^\zeta ||\phi(\mathbf{X}^{(m)}) - \mathbf{V}_m \mathbf{U}||_F^2$$
$$s.t. \ \mathbf{V}_m{}^\top \mathbf{V}_m = \mathbf{I}_q. \tag{26}$$

Then, Eq. (26) can be rewritten as,

$$\min_{\mathbf{V}_m{}^\top \mathbf{V}_m = \mathbf{I}_q} tr(-2\mu_m{}^\zeta \phi(\mathbf{X}^{(m)}) \mathbf{U}^\top \mathbf{V}_m{}^\top + \mu_m{}^\zeta \mathbf{V}_m \mathbf{U} \mathbf{U}^\top \mathbf{V}_m{}^\top). \tag{27}$$

We introduce an auxiliary variable $\mathbf{K}_m$, and set $\mathbf{K}_m = \mathbf{V}_m$. Then, Eq. (27) can be rewritten as,

$$\min_{\mathbf{V}_m{}^\top \mathbf{V}_m = \mathbf{I}_q} tr(-2\mu_m{}^\zeta \phi(\mathbf{X}^{(m)}) \mathbf{U}^\top \mathbf{V}_m{}^\top + \mu_m{}^\zeta \mathbf{K}_m \mathbf{U} \mathbf{U}^\top \mathbf{V}_m{}^\top)$$
$$+ \frac{\lambda}{2} ||\mathbf{V}_m - \mathbf{K}_m + \frac{\mathbf{\Lambda}_{\mathbf{V}m}}{\lambda}||_F^2, \tag{28}$$

where $\mathbf{\Lambda}_{\mathbf{V}m}$ is the difference between the auxiliary variable and target variable, $\lambda > 0$ is the trade-off parameter. Then Eq. (28) can be obtained by,

$$\min_{\mathbf{V}_m{}^\top \mathbf{V}_m = \mathbf{I}_q} tr \left(-2\mu_m{}^\zeta \phi(\mathbf{X}^{(m)}) \mathbf{U}^\top \mathbf{V}_m{}^\top + \mu_m{}^\zeta \mathbf{K}_m \mathbf{U} \mathbf{U}^\top \mathbf{V}_m{}^\top \right.$$
$$\left. -\lambda \mathbf{V}_m{}^\top (\mathbf{K}_m - \frac{\mathbf{\Lambda}_{\mathbf{V}m}}{\lambda}) \right). \tag{29}$$

Eq. (29) can be transformed as,

$$\max_{\mathbf{V}_m{}^\top \mathbf{V}_m = \mathbf{I}_q} tr \left(\mathbf{O} \mathbf{V}_m{}^\top \right), \tag{30}$$

where $\mathbf{O} = 2\mu_m{}^\zeta \phi(\mathbf{X}^{(m)}) \mathbf{U}^\top - \mu_m{}^\zeta \mathbf{K}_m \mathbf{U} \mathbf{U}^\top + \lambda \mathbf{K}_m - \mathbf{\Lambda}_{\mathbf{V}m}$. The optimal $\mathbf{V}_m$ can be solved by $\mathbf{V}_m = \mathcal{P} \mathcal{Q}^\top$, where $\mathcal{P}$ and $\mathcal{Q}$ are composed of left-singular and right-singular of $\mathbf{O}$, respectively.

$\mathbf{K}_m$-**step**: The objective function of $\mathbf{K}_m$ can be obtained as,

$$\max_{\mathbf{K}_m{}^\top \mathbf{K}_m = \mathbf{I}_q} tr(\mathbf{O}_k \mathbf{K}_m{}^\top), \tag{31}$$

where $\mathbf{O}_k = -\mu_m{}^\zeta \mathbf{V}_m{}^\top \mathbf{U} \mathbf{U}^\top + \lambda \mathbf{V}_m + \mathbf{\Lambda}_{\mathbf{V}m}$. The optimal solution of $\mathbf{K}_m$ is $\mathcal{P}_k \mathcal{Q}_k{}^\top$, where $\mathcal{P}_k$ and $\mathcal{Q}_k$ are

composed of left-singular and right-singular of $\mathbf{O}_k$, respectively.

$\mathbf{\Lambda}_{\mathbf{V}m}$-**step**: The update rule of $\mathbf{\Lambda}_{\mathbf{V}m}$ is,

$$\mathbf{\Lambda}_{\mathbf{V}m} = \mathbf{\Lambda}_{\mathbf{V}m} + \lambda(\mathbf{V}_m - \mathbf{K}_m). \tag{32}$$

iv. The second step of **A2LH**

Our proposed method is a two-step hashing, so in the second step, we need to learn the hash map hash by the hash code generated in the first step. Hash functions can be linear mapping functions, deep neural networks, support vector machine, etc. In order to accelerate and simplify the learning process of hash function, linear hash mapping function is used in this paper. Specifically, the learning process of hash function can be done by the following,

$$\min_{\mathbf{W}_m} ||\mathbf{B} - \mathbf{W}_m \phi(\mathbf{X}_m)||_F^2 + \omega ||\mathbf{W}_m||_F^2, \tag{33}$$

where ω is a regularization parameter. The optimal solution of the variable $\mathbf{W}_m \in \mathbb{R}^{k \times q}$ is,

$$\mathbf{W}_m = \mathbf{B} \phi(\mathbf{X})^\top (\phi(\mathbf{X}) \phi(\mathbf{X})^\top + \omega \mathbf{I})^{-1}. \tag{34}$$

v. Time Cost Analysis

In this section, we analyze the time consumption of the variables in the two stages of the **A2LH**, where the objective function involves a total of seven variables, i.e., $\mathbf{R}, \mathbf{C}, \mathbf{B}, \mathbf{U}, \mathbf{V}_m, \mathbf{W}_m$. In the training stage, the time cost of solving $\mathbf{R}$ is $\mathcal{O}(kqn + k^2q + k^3 + kcn + c^2n + kc^2 + c^3 + kc + k^2c)$, the time cost of solving $\mathbf{C}$ is $\mathcal{O}(kcn + k^2c + k^3 + kcq + qcn + q^2n + q^3 + k^2q + kq^2 + kn + qn + kq)$, the time of solving $\mathbf{B}$ is $\mathcal{O}(kqn)$, the time complexity of solving $\mathbf{U}$ is $\mathcal{O}(qkc + qcn + q^2k + q^2n + qkn + q^3)$, the time complexity of solving $\mathbf{V}_m$ is $\mathcal{O}(q^2n + q^3)$. In the inference stage, the time cost of solving $\mathbf{W}$ is $\mathcal{O}(q^2n + q^3 + kq^2 + kqn)$. Assume $q, k, c, T \ll n$, where T is the number of iterations. Therefore, it can be easily concluded that the overall time complexity of our proposed **A2LH** is linear in the number of instances, i.e., n.

IV. Experimental Results

Algorithm 1: Adaptive Asymmetric Label-guided Hashing (A2LH)

Input   : The multimedia data features $\mathbf{X}^{(m)}$, parameters $\alpha, \beta, \zeta, \eta, \lambda$, and maximal iteration number T.
Output: Binary code $\mathbf{B}$, Hash function $\mathbf{W}_m$.

1 **Procedure:**
2 *% The first step of A2LH*
3 **Initialization:** Compute the kernel-based data features via Eq. (1), initialize the variables $\mu_m, \mathbf{R}, \mathbf{C}, \mathbf{B}, \mathbf{U}, \mathbf{V}_m, \mathbf{K}_m$ and $i = 1$.
4 **while** $i < T$ *and not converged* **do**
5      $t = 1$;
6   Update μ_m via (12);
7   Update $\mathbf{R}$ via (15);
8   Update $\mathbf{C}$ via (18);
9   Update $\mathbf{B}$ via (22);
10   Update $\mathbf{U}$ via (25);
11   Update $\mathbf{V}_m$ via (30);
12   Update $\mathbf{K}_m$ via (31);
13      $i = i + 1$;
14 **end**
15 *% The second step of A2LH*
16 Update $\mathbf{W}_m$ via (34);

---

i. Dataset Descriptions

We validate our proposed **A2LH** with two publicly available datasets, i.e., MIRFlickr and NUS-WIDE datasets.

1. **MIRFlickr dataset** consists of 25k instances obtained from Flick.com. Each instance is labelled as some of 24 tags. Each text modality data is characterized by a 1,386-dim Bag-of Words (BoW) feature vector and each image modality data is characterized by a 512-dim GIST feature vector.

2. **NUS-WIDE dataset** contains 269,648 instances with 81 different tags. We select the top 10 most used tags, then obtain a subset consisting of 186,577 instances. Each text modality data is characterized by a 1,000-dim Bag-of Words (BoW) feature vector and each image modality data is characterized by a 500-dim Bag-of-Visual Words (BoVW) feature vector.

ii. Baselines and Implementation Details

The state-of-the-art methods compared in this paper are broadly classified into two categories, unsupervised

Table 2: *Performance comparison on MIRFlickr-25K measured by mAP.*

Task	Method	16 bits	32 bits	64 bits	128 bits
I→T	CMFH	0.5687	0.5680	0.5685	0.5687
	SCM-seq	0.6373	0.6478	0.6537	0.6611
	SePH-km	0.6685	0.6818	0.6830	0.6873
	FSH	0.6016	0.6149	0.6194	0.6242
	TECH	0.7304	0.7478	0.7553	0.7615
	SRLCH	0.6234	0.6328	0.6271	0.6561
	MTFH	0.7489	0.7533	0.7578	0.7631
	LESGH	0.7512	0.7598	0.7621	0.7759
	A2LH	**0.7531**	**0.7638**	**0.7717**	**0.7845**
T→I	CMFH	0.5615	0.5606	0.5606	0.5608
	SCM-seq	0.6206	0.6298	0.6372	0.6427
	SePH-km	0.7076	0.7212	0.7293	0.7348
	FSH	0.5979	0.6114	0.6186	0.6251
	TECH	0.8000	0.8241	0.8361	0.8449
	SRLCH	0.6052	0.6161	0.6412	0.6021
	MTFH	0.7933	0.8016	0.8147	0.8264
	LESGH	0.8126	0.8185	0.8203	0.8290
	A2LH	**0.8133**	**0.8253**	**0.8262**	**0.8328**

Table 3: *Performance comparison on NUS-WIDE measured by mAP.*

| Task	Method	16 bits	32 bits	64 bits	128 bits
I→T	CMFH	0.3437	0.3399	0.3409	0.3440
	SCM-seq	0.5120	0.5422	0.5488	0.5483
	SePH-km	0.5537	0.5627	0.5622	0.5698
	FSH	0.3732	0.3894	0.4014	0.4084
	TECH	0.6221	0.6375	0.6450	0.6415
	SRLCH	0.3578	0.3604	0.3671	0.3752
	MTFH	0.5921	0.6087	0.6246	0.6221
	LESGH	0.6221	0.6336	0.6389	0.6451
	A2LH	**0.6298**	**0.6388**	**0.6497**	**0.6507**
T→I	CMFH	0.3498	0.3435	0.3486	0.3529
	SCM-seq	0.4836	0.5067	0.5141	0.5161
	SePH-km	0.6407	0.6515	0.6608	0.6651
	FSH	0.3717	0.3835	0.3973	0.4007
	TECH	0.7665	0.7858	0.7975	0.7950
	SRLCH	0.3600	0.3641	0.3514	0.3676
	MTFH	0.6791	0.6973	0.7187	0.7191
	LESGH	0.7474	0.7643	0.7812	0.7884
	A2LH	**0.7698**	**0.7942**	**0.8032**	**0.8057**
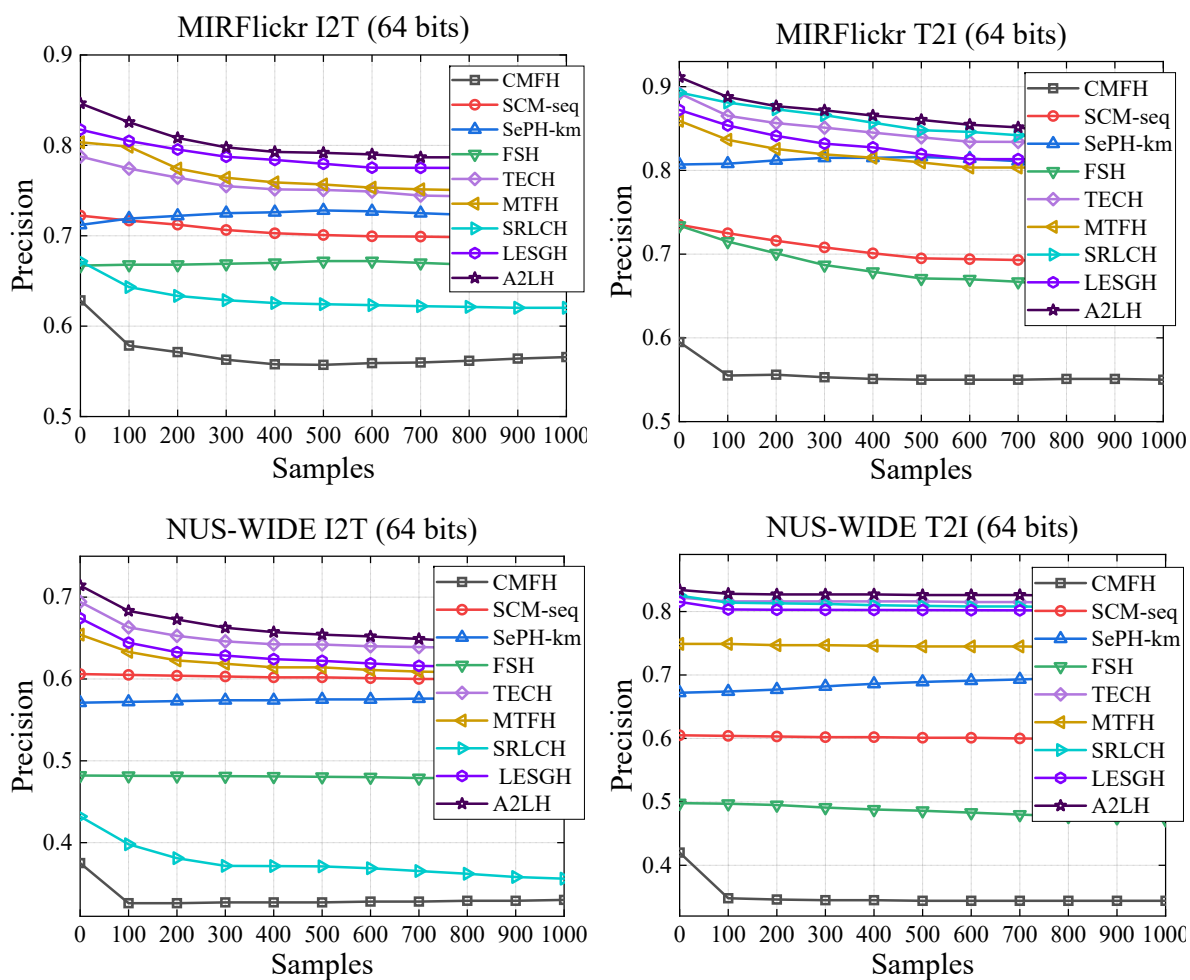
Figure 1: *The top-n precision curves of all methods on the MIRFlickr and NUS-WIDE datasets with the code length of 64 bits.*

hashing and supervised hashing. Specifically, unsupervised hashing methods are **CMFH** [5] and **FSH** [21] and supervised hashing methods are **SCM-seq** [54], **SePH-km** [18], **TECH** [4], **SRLCH** [34], **MTFH** [25] and **LESGH** [27].

The proposed **A2LH** in this paper has the following parameters, i.e., ζ, α, β, η and λ. The optimal parameters are set as $\zeta = 2$, $\alpha = 10^{-2}$, $\beta = 10^{1}$, $\eta = 10^{-3}$ and $\lambda = 10^{-4}$. The number of instances selected for kernelization, i.e., q, is set to 2500.

iii. Metrics

In this paper, we focus on two types of retrieval tasks, i.e., retrieving texts by the use of image query (I2T) and retrieving images by the use of text query (T2I). Two broad evaluation metrics are used, i.e., mAP and P@n. Specifically, mAP is defined as,

$$mAP = \frac{1}{O_q}\frac{1}{P_q}\sum_{i=1}^{O_q}\sum_{i=1}^{n} Pre(i) \times \mathbb{Y}_q(i), \qquad (35)$$

where O_q is the number of query, P_q is the similar instances in the dataset, n is the number of dataset, $Pre(i)$ denotes the precision of returned top i instances, $\mathbb{Y}_q(i)$ represents the indicator operation, i.e., $\mathbb{Y}_q(i) = 1$ means that the i-th returned instance is related to the query, and vice versa.

iv. Results

The results of mAP are shown in Table 2 3. From the tables, it can be observed that,

1. Supervised hash learning methods, i.e., CMFH and FSH, are superior to unsupervised ones, i.e., SCM-seq, SePH-km, TECH, SRLCH, MTFH, LSEGH, **A2LH**. The reason is because supervised hash learning methods consider semantic labels, which greatly enhances the discriminative power of hash code generation.

2. With the increase of hash codes, the retrieval performance is gradually improving. However, as the code bit length increases to a certain level, the retrieval performance does not improve significantly. The reason is due to the fact that as the hash code length increases, more information can be accommodated, but longer hash codes also increase noise,

such as quantization error accumulation and other factors.

3. The reason why our proposed method is significantly better than the other compared state-of-the-art methods is that we incorporate both the common latent representation of different modalities and the label semantic representation into the learned hash codes to improve their discriminative power. In addition, we leverage a discrete optimization strategy to solve the problem of quantization loss caused by the relaxation-based strategy.

In addition, we also plotted P@n curves when the hash code length is 64 bits on the NUS-WIDE dataset in Fig. 1. Higher curves indicate better performance. From the figures, we can see that our proposed method is superior to the other methods.

v. Comparison with Deep Cross-modal Hashing

Due to the significant success of deep neural networks in the field of representation learning, and some deep cross-modal hashing methods have been proposed in the recent years. In this subsection, we present a variant of **A2LH**, i.e., **A2LH**-D, and compare it with some state-of-the-art deep cross-modal hashing methods, i.e., RDCMH [26], NrDCMH [43] and DCHUC [40]. Specifically, we first extract the deep features of the image data using VGG-Net [37] as image-modality representation. Thereafter, the deep 4,096d vector image modality and the original text representation for training. The mAP results are shown in Table 4. It can be seen from the table, our proposed **A2LH**-D achieves the best performance compared to the state-of-the-art deep methods, even though our proposed **A2LH**-D is not an end-to-end learning strategy. The reason is that the deep image features contain rich deep semantic information and we use a discrete optimization strategy approach to solve the quantization error problem caused by the discrete optimization-based strategy employed by the deep hashing methods.

vi. Ablation Experiments

vi.1 Effects of Kernelization

The purpose of kernelization (see Sec. ii.1) is to ensure potential nonlinear correlations within the different

Table 4: *The mAP values of A2LH-D and some deep hashing with VGG-19 features on NUS-WIDE dataset.*

Task	I→T			T→I		
Method	16 bits	32 bits	64 bits	16 bits	32 bits	64 bits
RDCMH	0.6123	0.6213	0.6300	0.6510	0.6598	0.6357
NrDCMH	0.6023	0.6078	0.6234	0.6432	0.6534	0.6341
DCHUC	0.7335	0.7576	0.7830	0.6689	0.6995	0.7321
A2LH-D	**0.7509**	**0.7712**	**0.8023**	**0.6831**	**0.7110**	**0.7413**

modalities. In order to verify the effect of kernelization operation on different modalities, in this subsection, we design a variant of **A2LH**, named **A2LH**-K, which removes the kernelization operation and perform hash code learning and hash function generation directly with the original features of different modalities. Specifically, the overall objective function (9) can be rewritten as,

$$\min_{\mu_m, \mathbf{R}, \mathbf{C}, \mathbf{B}, \mathbf{U}, \mathbf{V}_m} ||(\mathbf{R}\mathbf{L})^\top \mathbf{C}\mathbf{U} - k\mathbf{S}||_F^2 + \alpha ||\mathbf{B} - \mathbf{C}\mathbf{U}||_F^2$$
$$+ \beta ||\mathbf{R}\mathbf{L} - \mathbf{B}||_F^2 + \mu_m{}^\zeta ||\mathbf{X}^{(m)} - \mathbf{V}_m \mathbf{U}||_F^2 + \eta \mathcal{R}(\mathbf{R}\mathbf{L}, \mathbf{U})$$
$$s.t.\ \mathbf{B} \in \{-1, 1\}^{k \times n},\ \mathbf{V}_m{}^\top \mathbf{V}_m = \mathbf{I}_q, \sum_m \mu_m = 1, \mu_m > 0, \tag{36}$$

vi.2 Effects of Multi-Semantic Space Learning

The multi-label space learning module is designed to refine the semantic association relationships between different modalities, while embedding the rich semantic information in the labels into the hash codes. In order to verify the effects of multi-label space learning module on the quality of hash code generation, in this subsection, we design a variant of **A2LH**, named **A2LH**-M, which removes the relevant module for verification. Specifically, the overall objective function (9) can be rewritten as,

$$\min_{\mu_m, \mathbf{R}, \mathbf{C}, \mathbf{B}, \mathbf{U}, \mathbf{V}_m} ||\mathbf{B}^\top \mathbf{C}\mathbf{U} - k\mathbf{S}||_F^2 + \alpha ||\mathbf{B} - \mathbf{C}\mathbf{U}||_F^2$$
$$+ \mu_m{}^\zeta ||\phi(\mathbf{X}^{(m)}) - \mathbf{V}_m \mathbf{U}||_F^2 + \eta \mathcal{R}(\mathbf{U})$$
$$s.t.\ \mathbf{B} \in \{-1, 1\}^{k \times n},\ \mathbf{V}_m{}^\top \mathbf{V}_m = \mathbf{I}_q, \sum_m \mu_m = 1, \mu_m > 0, \tag{37}$$

vi.3 Effects of Discrete Optimization Scheme

The use of discrete optimization strategy to generate hash codes can avoid the quantization errors. To verify the effectiveness of the discrete optimization strategy,

Table 5: *The ablation results of A2LH on the NUS-WIDE dataset with various code lengths.*

Task	Method	16 bits	32 bits	64 bits	128 bits
I→T	**A2LH**-K	0.6268	0.6309	0.6370	0.6444
	A2LH-M	0.6190	0.6198	0.6291	0.6404
	A2LH-B	0.5900	0.6156	0.6189	0.6223
	A2LH	**0.6298**	**0.6388**	**0.6497**	**0.6507**
T→I	**A2LH**-K	0.7646	0.7813	0.7887	0.7936
	A2LH-M	0.7551	0.7752	0.7812	0.7879
	A2LH-B	0.7328	0.7526	0.7680	0.7803
	A2LH	**0.7698**	**0.7942**	**0.8032**	**0.8057**

we design a variant of **A2LH**, named **A2LH**-B, which first treats the hash codes **B** as real-value matrix and then uses a threshold function to process them, i.e., $\tilde{\mathbf{B}} = sgn(\mathbf{B})$. Specifically, the solution of Eq. (22) can be rewritten as,

$$\mathbf{B} = \frac{\alpha \mathbf{C}\mathbf{U} + \beta \mathbf{R}\mathbf{L}}{\alpha + \beta}. \tag{38}$$

Table 5 reports the mAP results on the NUS-WIDE dataset with various lengths. From the table, it can be shown that (1) removing the kernelization operation leads to a degradation in the retrieval performance of hash codes due to the fact that the kernelization operation can mine the complex association relationships within different modalities and improve the generated hash code discriminative capabilities. (2) Removing the multi-semantic space learning module also leads to a decrease in retrieval performance, because the multi-semantic space learning module can improve the semantics of the generated hash codes, which in turn improves the quality of hash code generation. (3) The use of hash code optimization strategies based on relaxation strategies can lead to severe retrieval performance degradation due to the large quantization errors caused by optimization methods based on relaxation strategies.
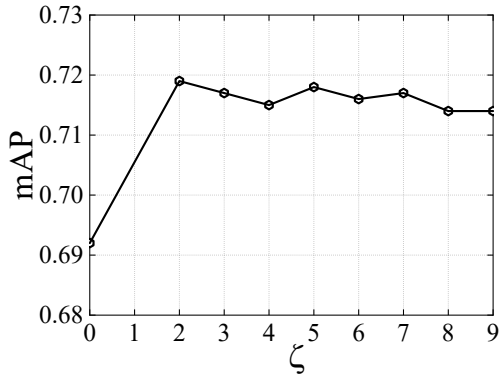
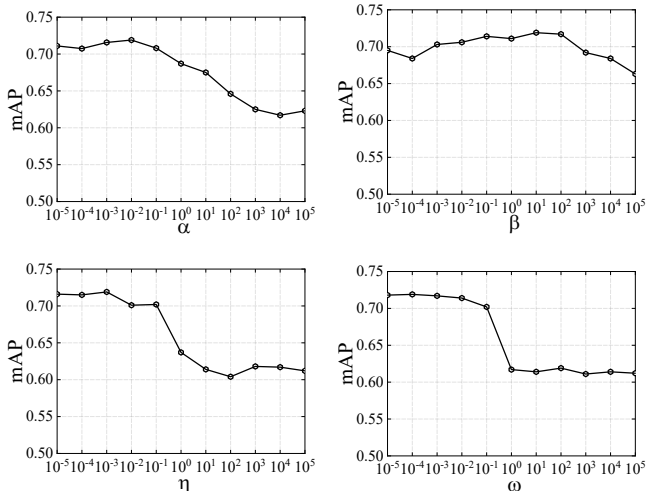**Figure 2:** *Parameter sensitivity analysis of ζ on the NUS-WIDE dataset@ 32 bits..*

Figure 3: *Parameter sensitivity analysis of α, β, η, ω on the NUS-WIDE dataset@ 32 bits.*
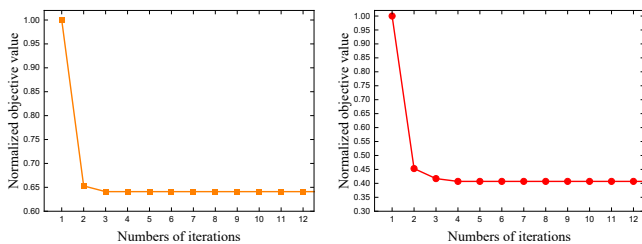

Figure 4: *Convergence curves of **A2LH** on two datasets with 64 bits. **Left**: MIRFlickr dataset, **Right**: NUS-WIDE dataset.*

vii. Parameter Sensitivity Analysis

In order to assess the impact of parameters on model performance, we performed a relevant parameter sensitivity analysis on the MIRFlickr dataset. Specifically, one of the parameters to be evaluated is updated by fixing other parameters. The length of the hash codes is set to a fixed 64 bits. The values of parameters α, β, η and ω are set in the range of $\{10^{-5}, 10^{-4}, ..., 10^4, 10^5\}$ and the values of the parameter ζ is set in the range of $\{0, 2, 3, 4, ..., 9\}$. The mAP results are shown in Fig. 2 and 3. From the figures, it can be observed that (1) the exponential parameter ζ is very stable in the ranges of $[2, 9]$. It is worth noting that when $\zeta = 0$, i.e., neglecting the contribution of different modalities to the common latent representation, it causes a large performance degradation. The experimental results demonstrate the effectiveness of our proposed dynamic contribution weighting strategy. (2) The parameters α, β, η and ω are very stable over a wide range of values. Specifically, the parameter α is stable in the range of values $[10^{-5}, 10^{-1}]$; the parameter β is stable in the range of values $[10^{-5}, 10^2]$; the parameter η is stable in the range of values $[10^{-5}, 10^{-3}]$; the parameter α is stable in the range of values $[10^{-5}, 10^{-1}]$. In summary, our proposed **A2LH** can be easily deployed to practical applications.

viii. Convergence Analysis

To verify the convergence of our proposed optimization algorithm, we will conduct convergence analysis experiments on MIRFlickr dataset. The values of the objective function (9) are plotted in Fig. 4. From the figure, it can be found that our proposed algorithm reaches convergence quickly, with less than 5 iterations, the reason is that all variables of the proposed algorithm have analytic solutions. Note that the values of objective function are normalized to between 0 and 1.

V. Conclusion

This paper presents a novel discrete hashing method, termed **A**daptive **A**symmetric **L**abel-guided **H**ashing (**A2LH**). We design an asymmetric discrete hash learning framework that links the common latent representations of different modalities with label embeddings in a clever way, by which learning will greatly improve the discriminative power of hash codes and

thus the retrieval performance. In addition, an efficient discrete optimization algorithm is proposed to solve the optimization problem of hash code learning, and the proposed method can compensate the problems of quantization error and low learning rate. Adequate experimental results show that our proposed method significantly outperforms the compared state-of-the-art methods, thus validating the effectiveness of our method. In the future, we will incorporate contrast learning techniques to improve the robustness of hash code learning.

Acknowledgment

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