Generalized Semantic Preserving Hashing for Cross-Modal Retrieval
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Abstract—Cross-modal retrieval is gaining importance due to the availability of large amounts of multimedia data. Hashing-based techniques provide an attractive solution to this problem when the data size is large. For cross-modal retrieval, data from the two modalities may be associated with a single label or multiple labels, and in addition, may or may not have a one-to-one correspondence. This work proposes a simple hashing framework which has the capability to work with different scenarios while effectively capturing the semantic relationship between the data items. The work proceeds in two stages in which the first stage learns the optimum hash codes by factorizing an affinity matrix, constructed using the label information. In the second stage, ridge regression and kernel logistic regression is used to learn the hash functions for mapping the input data to the bit domain. We also propose a novel iterative solution for cases where the training data is very large, or when the whole training data is not available at once. Extensive experiments on single label data set like Wiki and multi-label datasets like MirFlickr, NUS-WIDE, Pascal, and LabelMe, and comparisons with the state-of-the-art, shows the usefulness of the proposed approach.

Index Terms—Cross-modal retrieval, hashing, multi-label data, unpaired matching scenarios, kernel logistic regression.

I. INTRODUCTION

ROSS-MODAL retrieval tasks are very important in the field of computer vision due to the availability of large amounts of multimedia data. For example, given an image query, it is often required to retrieve relevant textual documents from the database. Due to the richness of multimedia data, it is often designated with multiple labels that can better capture the information compared to just a single label (Fig. 1(a,b)). In addition, real-life data is often unpaired without one-to-one correspondences. For example, say ten text and five image data samples belong to the same category, which means that the image and text data cannot be paired, though class-wise pairing is still possible. The cross-modal retrieval tasks, in general, can be subdivided roughly into the following four categories - (1) single label paired (SL-P), where the one-to-one correspondence between samples of the two modalities is present, (2) single label unpaired (SL-U) where such pairing is absent, (3) multi-label paired (ML-P) where the data is multi-label along with pair information and (4) multi-label unpaired (ML-U) where the number of multi-label data items is different in both the modalities. (Fig. 1(c,d,e,f)).

The paired scenario cases have been extensively studied in the literature for both supervised frameworks where the labels are provided [22], and unsupervised frameworks where the labels are absent [8]. For unpaired scenarios, approaches in [20] and [22] have been proposed to handle the SL-U and ML-U cases respectively. Recently, hashing techniques, whose main objective is to generate good binary encodings to capture the semantic relations between the data, have gained popularity because of their impressive retrieval results, low-storage costs and efficient retrieval. Hashing techniques for both unsupervised [5] [26] [36] [37] and supervised settings [3] [13] [31] [37] for the SL-P and ML-P problems have been proposed. To the best of our knowledge, the task of SL-U and ML-U are yet to be addressed by the hashing based approaches in the computer vision community.

This work proposes a generalized hashing approach for cross-modal retrieval which has the capability to work under the different scenarios listed above, while respecting the structural and semantic relationships between the data. Our work is inspired by the success of the recent techniques in [14], where it was shown that a two-stage hashing framework allows for greater control and flexibility in designing the two stages of the algorithm. The work in [29] also showed that a two-stage formulation can cut down the model complexity, thus enabling a simpler procedure to solve it. In the first stage, we capture the semantic relations between the data items of the two modalities by encoding the label information in an affinity matrix. The algorithm then learns the optimum hash codes simultaneously for the two modalities by minimizing a non-convex optimization problem. We propose different strategies for solving the first stage, which greatly speeds up the hash code learning and enables us to utilize a larger training set, if available. For the second stage, we use linear regression and kernel logistic regression to learn the hash functions. We propose schemes for out-of-sample extensions and unifying the learned hash codes for the SL-P and ML-P settings. In addition, we propose a new framework to handle very large training data in an iterative fashion. This is also useful when the whole training data is not available initially (becomes available gradually). Extensive experiments on five image-text datasets, Wiki [21], MirFlickr [9], NUS-WIDE [4], Pascal [6] and LabelMe [23] and comparisons with state-of-the-art
techniques shows the effectiveness of the proposed approach. The main contributions of this work can be summarized as follows:

1) We propose a generalized hashing scheme which can seamlessly handle the different scenarios like SL-P, SL-U, ML-P and ML-U in the same framework.
2) To the best of our knowledge, this is the first work on hashing to handle the SL-U and ML-U task.
3) We propose an iterative framework to handle very large data during the training stage.
4) Extensive experiments show that the proposed approach compares favorably with respect to the state-of-the-art.

A preliminary version of this work appeared in [17]. The main additions in this work from [17] are: (1) We propose two efficient ways for learning the hash codes in stage 1, (2) We propose a new unification strategy for hash codes which gives superior performance, (3) We propose an iterative approach to handle large amounts of training data in a batch-wise fashion. (4) We also present results on the MirFlickr dataset [9].

The rest of this paper is organized as follows. Section II discusses the related works. Section III gives details of the proposed approach. The experiments and analysis are given in Section IV. The paper concludes with a brief summary.

II. RELATED WORK

Here we provide pointers to some of the related work. A good discussion on the recent cross-modal and hashing techniques are provided in [18] [27].

**Cross-Modal Approaches:** CCA [8] and its variants have been developed for cross-modal matching problems and have gained immense popularity due to its impressive performance. It is an unsupervised approach applicable for the SL-P setting. A modified version of CCA, Cluster CCA [22] utilizes the class labels and thus can handle SL-U data. With the availability of ever-expanding multimedia data, the need for algorithms which can handle multi-label data both in paired and unpaired settings arose, which led to the development of the FCCA algorithm [20]. FCCA [20] is a general version of CCCA [22] and reduces to the CCCA formulation in the presence of single label data. A cross-modal correlation learning algorithm [19] which uses multi-grain fusion within a hierarchical framework has shown promise in cross-modal retrieval applications.

**Hashing Based Approaches:** Hashing based approaches can be broadly divided into supervised and unsupervised ones. In unsupervised hashing, the hash codes are learned so as to preserve the inter-modality and intra-modality information present in the training data [5] [26] [36] [37]. Inter-media hashing [26] map features from different modalities into the common Hamming domain. Collective matrix factorization hashing (CMFH) [5] decomposes the data from different modalities into a unified hash code. Sparse coding and matrix factorization are used in latent semantic sparse hashing (LSSH) [36] for image and text representation, which are then mapped to a joint space to generate the unified hash code. The similarity-agreement criterion has been used to learn the hash codes separately for both the modalities in [3]. In cross view hashing (CVH) [13], hash functions are learned to minimize the similarity-weighted Hamming distances between the hash codes of training data. The hashing framework in a probabilistic setting has been proposed in [35]. Quantization techniques for this task giving good performance have also been proposed [16] [28] [34]. Generative Adversarial Networks have also been used to capture the structure of the cross-modal data for hashing in [33].

Well known supervised methods like CMSSH [3] and CVH [13] leverage the label information for getting better performance. The label information in SePH [15] after being encoded into an affinity matrix is transformed to a probability distribution from which approximate hash codes are learned while minimizing the Kullback-Leibler divergence. The hashing based approaches typically work in the SL-P and ML-P mode, where there is a one-to-one correspondence between the data of the two modalities. The work in [30] exploits the discriminative capability of the class labels during the hash function learning stage and incorporates the discrete constraints on the binary codes to further reduce the quantization error. Considering the input data to be paired, in many techniques [15] [16], common hash codes are learned for both the modalities, instead of separate codes [3] [31].
A semi-supervised hashing technique [32] have been proposed which can exploit both the labeled and unlabeled examples.

Instead of learning the optimal hash codes and mapping functions in a joint optimization framework, some works [14] [15] [29] decompose the problem into two sub-problems, which often lead to simpler formulations. The first sub-problem deals with learning the hash codes and the second one deals with learning the hash functions. In this work, a generalized hashing technique has been proposed, which can seamlessly work with both single and multi-label data and has the capability of handling both the paired and unpaired scenarios. To the best of our knowledge, this is the first attempt at developing a hashing technique for the unpaired scenario.

III. THE PROPOSED APPROACH

A. Notation

In this work, $X$ represents a matrix, $x_j$ represents the $j^{th}$ column of the matrix and $x_{ij}$ represents its $(i, j)^{th}$ element. $\| \cdot \|_F$ denotes the Frobenius norm: $\| X \|_F^2 = \text{Tr}(X^T X)$. The operation $X^* = \text{Proj}_{[-1, 1]} X$ denotes the following

$$
x^*_{ij} = \begin{cases} 
-1, & \text{if } x_{ij} < -1, \\
x_{ij}, & \text{if } x_{ij} \in [-1, 1], \\
1, & \text{if } x_{ij} > 1.
\end{cases}
$$

The sign operation is defined as $\text{sign}(x_{ij}) = 1$ if $x_{ij} \geq 0$, and $-1$ otherwise. Vector and matrix operations using $\text{Proj}$ and $\text{sign}$ is implemented point-wise.

B. The Four Scenarios

Here we describe in details the proposed hashing framework. Let the two modalities be denoted as $X \in \mathbb{R}^{N_1 \times d_x}$ and $Y \in \mathbb{R}^{N_2 \times d_y}$, with $N_1, N_2$ being the number of items in either modality and $d_x, d_y$ being the dimensionality of the data (in general $d_x \neq d_y$) respectively. The labels for both the modalities $L_x \in \mathbb{R}^{N_1 \times C}$, $L_y \in \mathbb{R}^{N_2 \times C}$ are provided, where $C$ denotes the total number of categories. In case of single label data, only one of the $C$ entries is one (eg. $L^i_x = [0 \ 0 \ 1 \ 0 \ 0]$), while for multi-label data, more than one entry will be equal to one, (eg. $L^i_x = [1 \ 0 \ 1 \ 0 \ 1]$). Cross-modal retrieval tasks can be categorized as follows:

- **Single Label-Paired (SL-P):** Here, each sample from one modality has a corresponding sample in the other modality, i.e. $N_1 = N_2$, and each data belongs to one category. The affinity matrix $S$ of size $N_1 \times N_2$ is constructed as $S_{ij} = 1$ if $L^i_x = L^i_y$, else $S_{ij} = 0$.

- **Single Label-Unpaired (SL-U):** Here, though each sample belongs to one category, the pairing of data between the two modalities does not exist, and $N_1 \neq N_2$. Here $S$ is constructed similarly to SL-P.

- **Multi Label-Paired (ML-P):** Here, each sample from one modality has a corresponding sample in the other modality, i.e. $N_1 = N_2$, but each sample belongs to more than one category. Here $S$ can be constructed in several ways like (1) $S_{ij} = \langle L^i_x, L^j_y \rangle$, where $\langle \cdot, \cdot \rangle$ is the normalized inner product or as (2) $S_{ij} = e^{-r ||L^i_x - L^j_y||^2/\sigma}$, where $\sigma$ is a constant factor.

- **Multi Label-Unpaired (ML-U):** Here, each data sample belongs to multiple categories, but pairing of data between the two modalities does not exist, and $N_1 \neq N_2$. $S$ is constructed as in ML-P.

The objective is to find the optimal hash codes with similarity measure $S$. Then, we use linear ridge regression and kernel logistic regression to learn the hash functions.

C. Learning the Hash Code

Similar to our preliminary work [17], we factor the similarity matrix $S$ as $(1/q)A B^T$, where $A \in \mathbb{R}^{N_1 \times q}$ and $B \in \mathbb{R}^{N_2 \times q}$, $N_1$ and $N_2$ is the number of items in $X$ and $Y$, and $q$ is the length of the hash code. The hash codes for the items in $X$ (resp. $Y$) are given by the rows of $A$ (resp. $B$). Naturally, the elements of $A$ and $B$ are constrained to take values in $\{-1, 1\}$. Since it is not guaranteed that such a factorization exists, we consider the least squares problem:

$$
\min_{A, B} \| S - (1/q)A B^T \|_F^2 \\
\text{s.t. } A \in \{-1, 1\}^{N_1 \times q}, \quad B \in \{-1, 1\}^{N_2 \times q}.
$$

Unfortunately, (2) is a discrete optimization problem which is computationally intractable. A standard way is to use some suitable relaxation [29]. Here, we replace the constraint set $\{-1, 1\}$ by its convex hull, namely the interval $[-1, 1]$. This gives us the following surrogate of (2):

$$
\min_{A, B} \| S - (1/q)A B^T \|_F^2 \\
\text{s.t. } A \in [-1, 1]^{N_1 \times q}, \quad B \in [-1, 1]^{N_2 \times q}.
$$

We round the solution of (3) by taking the sign of the matrix elements to obtain the desired binary solution.

In [17], the optimization was solved by updating the bits element-wise. As a result, the approach is not computationally efficient (cf. Section IV-B). We propose two alternative approaches for solving (3): (i) updating entire columns, which also leads to a sub-problem that can be solved directly in the discrete domain, and (ii) updating the whole matrix in one shot. Now, we describe all the three techniques.

1) **Element update:** This procedure is followed in [17]. We note that, while the domain of (3) is convex, the objective is non-convex in variables $A$ and $B$. Nevertheless, due to the bilinear nature of the factorization, the objective is convex in $A$ if we hold $B$ fixed, and vice-versa. Thus, if one of the variables is held fixed, then (3) becomes a convex optimization problem in the other variable. This naturally leads to the idea of alternating minimization [38], where the variables are alternately updated holding the other variable fixed. To further improve the computational efficiency, we propose to use coordinate descent on top of alternating minimization. In particular, for some fixed $B$, we update the elements of $A$ in a sequential fashion [2]. While it is indeed possible to simultaneously update the elements of $A$ using projected gradient descent [2], this would be computationally expensive given the matrix size. In contrast, we now demonstrate how the coordinate-descent updates can be performed analytically (and in a parallel fashion) using simple closed-form expressions.
Consider a single alternating minimization step in which one of the variables, say \( B = [b_{ij}] \), is held fixed and we need to update \( A = [a_{ij}] \). As mentioned previously, we wish to use coordinate descent for this purpose, whereby the elements of \( A \) are updated one at a time, say, in a raster fashion. In particular, suppose that we wish to update the element \( a_{il} \). Notice that (3) can be expressed (up to a non-negative scaling) as

\[
\sum_{j=1}^{N_2} \left( R^j_i + a_{il}b_{jl} \right)^2 + \text{const. terms},
\]

where the constant terms do not depend on \( a_{il} \), and

\[
R^j_i = \sum_{k=1, k \neq i}^q a_{ik}b_{jk} - qS_{ij}.
\]

Therefore, the coordinate descent with respect to \( a_{il} \) results in the subproblem

\[
\min_{a_{il} \in [-1,1]} \sum_{j=1}^{N_2} \left( R^j_i + a_{il}b_{jl} \right)^2. \tag{4}
\]

This is a convex problem, involving minimization of a convex quadratic function over an interval. The objective in (4) can be expressed as

\[
\min_{a_{il}} \sum_{j=1}^{N_2} \left( a_{il}^2 + 2a_{il}R^j_i b_{jl} \right) + \text{const. terms} = \min_{a_{il}} a_{il} \sum_{j=1}^{N_2} \left( a_{il} + \frac{1}{\alpha} R^j_i b_{jl} \right)^2 + \text{const. terms} \tag{5}
\]

where \( b_{jl}^2 = a \). Clearly, the unconstrained minimum of (4) is attained at

\[
\hat{a}_{il} = -\frac{\sum_{j=1}^{N_2} R^j_i b_{jl}}{\sum_{j=1}^{N_2} b_{jl}^2}, \tag{6}
\]

which is precisely the point where the gradient of the objective in (4) is zero. Since the objective is a quadratic function with positive curvature\(^{1}\), it is not difficult to verify that the unique point where the minimum of (4) is attained is simply the projection of (6) onto \([-1,1]\) and is given by

\[
a_{il}^\ast = \text{Proj}_{[-1,1]} \hat{a}_{il}. \tag{7}
\]

Notice that the denominator of (6) can be precomputed for each row update (during which \( i \) is fixed). Moreover,

\[
R^j_{i+1} = R^j_i - a_{il+1}b_{jl+1} + a_{il}^\ast b_{jl}. \tag{7}
\]

This relation can be used to further speed up the update of successive elements on a given row. An identical strategy is used for updating \( B \) (holding \( A \) fixed). The final hash codes are obtained by using the sign operation.

The overall algorithm is summarized in Algorithm 1. The outer loop corresponds to alternating minimization, while the inner loop corresponds to coordinate updates. An important point to note is that we use just one pass of coordinate descent (one raster update). This is because we noticed that the final solution does not substantially change if we use multiple passes. Next, we discuss the column-wise and matrix update versions of solving the same objective, which are computationally more efficient as compared to the element-wise update technique.

2) Column update: We observe that the hash bits can be independently learned in (3). We write \( A \) and \( B \) in column format as \( A = [a_1, \ldots, a_j, \ldots, a_q] \) and \( B = [b_1, \ldots, b_j, \ldots, b_q] \). Suppose we wish to update column \( a_j \). We can write (3) as

\[
||qS - \sum_{c \neq j}^q a_c b_c^T||_F^2 = ||P - a_j b_j^T||_F^2 = \text{Tr} \left[ P P^T - 2a_j b_j^T b_j a_j^T \right],
\]

where \( P = qS - \sum_{c \neq j}^q a_c b_c^T \). Setting \( a = b_j^T b_j \), the objective simplifies to

\[
a \left( ||a_j||^2 - 2 \frac{1}{\alpha} (Pb_j)^T a_j + \text{Tr} \left[ \frac{1}{\alpha} P P^T \right] \right) = a \left( ||a_j||^2 - \frac{1}{\alpha} P b_j \right)^2 + \text{constant terms}. \tag{8}
\]

It is easy to verify that the optimal solution is given by

\[
a_j^\ast = \text{Proj}_{[-1,1]} \left( \frac{1}{\alpha} P b_j \right). \tag{9}
\]

The entire process is summarized in Algorithm 2.

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\(^{1}\)We assume that \( \sum_{j=1}^{N_2} b_{j}^2 > 0 \), which is always the case in practice.
We also observe from the objective in (8), that we can actually solve the discrete version of the problem rather than the relaxed version of it as discussed earlier. For solving in the discrete domain, we observe that the first and the third terms in (8) are constant, and thus we need to solve the following

$$\max_{a_j \in \{-1, 1\}^p} 2(Pb_j)^T a_j$$

whose solution is given as

$$a_j^* = \text{sign}(2Pb_j).$$

3) Matrix update: If the column update discussed in the previous subsection can be replaced by matrix update, then the approach can be made even more computationally efficient. However, we observe that we cannot follow the same procedure as before as no closed form update is available in this case. Consider the expansion of (3) when we want to update matrix $A$ ($B$ is fixed)

$$\min_A \|AB^T - qS\|_F^2$$

$$= \min_A \text{Tr} \left( B^T B A - q S B A^T - q B^T S^T A + q^2 S^T S \right)$$

$$= \min_A \text{Tr} \left( P_1 A^T A - P_2 A^T - P_3 A + \text{const.} \right)$$

(11)

Setting the gradient equal to zero in (11) is not easy, because (11) cannot be decoupled in terms of only $A$. However, we observe that we cannot follow the same procedure as before as no closed form update is available in this case. Consider the expansion of (3) when we want to update matrix $A$ ($B$ is fixed)

$$\min_A \|AB^T - qS\|_F^2$$

$$= \min_A \text{Tr} \left( B^T B A - q S B A^T - q B^T S^T A + q^2 S^T S \right)$$

$$= \min_A \text{Tr} \left( P_1 A^T A - P_2 A^T - P_3 A + \text{const.} \right)$$

(11)

Setting the gradient equal to zero in (11) is not easy, because (11) cannot be decoupled in terms of only $A$ due to the presence of the term $P_1 A^T A$. This prohibits the use of closed form updates. We instead use projected gradient descent search (onto $\{ -1, 1 \}$), and at each gradient update, we compute the step length by computing analytically the Lipschitz constant. Though we are not using closed form updates, this method is more efficient because here, the entire matrix is getting updated in one shot.

The derivatives and Hessian of the function w.r.t $A$ (similarly for $B$) while keeping $B$ constant are given by

$$\nabla_A F(A) = 2AB^T B - 2qSB$$

$$H_A F(A) = 2B^T B$$

(12)

(13)

which leads to the following update rule

$$\tilde{A} = \left( A - \frac{1}{\lambda} \nabla_A \right) A^* = \text{Proj}_{[-1, 1]} \tilde{A}$$

(14)

The final hash codes are $X^* = \text{sign}(X)$ with $(X = A$ or $B$).

The value of $\lambda$ needs to be chosen appropriately. As the function is Lipschitz continuous, $\lambda$ can be setup in this way.\textsuperscript{2}

The entire process is summarized in Algorithm 3.

D. Learning the Hash Functions

In this step, we learn the hash functions independently for each bit. Though any classifier can be used for this purpose, here we use two standard approaches, namely (a) linear ridge regression with kernel preprocessing, and (b) kernel logistic regression to learn the mappings from the features to the hash codes for the input data, which we describe briefly below for completion. For the kernel preprocessing step, we follow the same protocol as in [25]. The anchors are chosen randomly.

1) Linear ridge regression: For linear ridge regression, we learn the functions to project the features $X_i$ into the hash code domain $A$ by solving the following equation

$$w_i^T = \min_{x} ||w_i - X_i||^2 + \mu ||z||^2$$

(15)

where, $z \in R^d_i$, is the ridge regression coefficients to be learned, and $\mu$ is a weight parameter for the regularization term. (15) has a closed form solution. Similarly, we compute the hash functions for the $Y$ modality.

2) Kernel logistic regression: Kernel logistic regression exploits the power of kernels to effectively learn a non-linear mapping function $W_X$ and $W_Y$. In KLR, kernels enable the mapping of $X_i$ to the Reproducing Kernel Hilbert Space (RKHS) as $\phi(X_i)$. We then learn linear functions in the RKHS space to enable us to go to the hash code domain. To learn the linear projection in RKHS for the $l$th bit ($1 \leq l \leq q$), we need to solve for $w_i^l$:

$$\min_{w_i^l} \sum_{i=1}^{N_i} \log(1 + e^{-a_i^l \phi(X_i) w_i^l}) + \lambda ||w_i^l||^2$$

(16)

where $\lambda$ is the parameter for the regularization term. The above function is solved using the minFunc solver [24].

First, either (15) or (16) is used to learn the hash functions for all the $q$ bits of the $X, Y$ modalities. They are collectively denoted as $W_X = \{w_1, w_2, ..., w_q\}$ and $W_Y = \{w_1, w_2, ..., w_q\}$, where $W_X = \{w_1^1, w_2^1, ..., w_q^1\}$ and $W_Y = \{w_1^2, w_2^2, ..., w_q^2\}$. During testing, given query $p \in R^d$, and gallery $G = \{g_1, g_2, ...\}$, $g_i \in R^d$, we use $W_X, W_Y$ to generate the hash codes as: $b^p = \text{sign}(p W_X)$ and $b^g_i = \text{sign}(g_i W_Y)$, for respectively.

E. Generation of unified hash codes

For the SL-P and ML-P case, where paired data from the two modalities are available, the learned hash codes can be unified appropriately for improved retrieval performance. Consider the $l$th bit, which needs to be unified for a given data $X_i$ and $Y_i$. For both LR and KLR, we can determine the likelihood of a bit being $\pm 1$ or $1$ given the sample $X_i$ and
Y_i [15]. The unified code \( c_{il} \) can be obtained as follows

\[
c_{il} = \text{sign}(0.5 \times (a_i^+ p(a_i = 1|X_i) - a_i^- p(a_i = -1|X_i)) + 0.5 \times (a_{il}^+ p(b_{il} = 1|Y_i) - a_{il}^- p(b_{il} = -1|Y_i)))
\]

where the constants \( \{a_i^+, a_i^-, a_{il}^+, a_{il}^-\} \) for \( l \in \{1, ..., q\} \) can be set by cross-validation. The constants are used to weigh the bits of the two modalities appropriately for getting better unified hash codes. The flowchart of the proposed algorithm is given in Fig. 1(g).

IV. EXPERIMENTS

Here, we report the results of extensive experiments performed to evaluate the effectiveness of the proposed approach for all the four scenarios discussed. Specifically, we report results on Wiki [21], which is a single-label dataset, and MirFlickr [9], NUS-WIDE [4], Pascal [6] and LabelMe [23] datasets, which are annotated with multiple labels. All the datasets considered here consist of image and text data, but this approach can be used in general for any other cross-modal tasks also. Next, we give a brief description of the datasets along with the features used. The evaluation protocol for the experiments has also been mentioned alongside.

A. Datasets and Evaluation Protocol

Wiki Dataset [21] consists of 2,866 image-text pairs encompassing data from 10 categories. Each data item has a single label out of the possible 10 categories. The images are described using 128-d SIFT descriptors and texts are represented as 10-d topic vectors. The dataset is split into 2,173 image-text pairs which serve as both the training and retrieval set and the other 693 pairs are used as the query set.

MirFlickr Dataset [9] contains 25,000 images and their corresponding text marked with 24 semantic labels collected from Flickr. Following the same protocol as in [15], we remove the textual information that appears in less than 20 images and also all images without textual tags or semantic labels to get a total corpus of 16,738 text-image pairs [15]. 150-d edge histogram and 500-d PCA reduced binary tagging vector are used as the features for image and text modality respectively. 5% of the pair serves as the query set while the rest is considered as the retrieval set [15].

NUS-WIDE Dataset [4] has 269,648 images described with multiple labels. Following the protocol in [15], we consider only the data from the top 10 most popular labels (about 186,577 pairs) in our experiments. For feature representation, we use 500-d bag-of-words for images and 1000-d vectors of the most frequent labels for textual descriptions. 4000 randomly sampled pairs from the whole dataset are randomly chosen to construct the query set while the rest is used as both the training and retrieval set.

LabelMe Dataset [23] consists of images marked with different tags and labels. From the available dataset of 3825 images, we perform a random 50 – 50 split to generate the training and testing sets as done in [20]. In accordance with the protocol in [20], bag of visual words, gist, color histogram and CNN features have been used as image features while the 209-d absolute tag rank has been used as the text features [10].

We have considered the ground truth annotation as the labels for the dataset.

Pascal Dataset [6] consists of 5011 train and 4952 test images. The same protocol as in [20] has been used here for our experiments including the same features over the provided train:test split.

For evaluation, we follow different performance measures while reporting the results, based on the different scenarios. For comparison against standard hashing techniques for SL-P and ML-P scenarios, we report the Mean Average Precision (MAP), i.e., the mean of the average precision of all the queries. Average precision is defined as \( \text{AP}(q) = \frac{\sum_{r=1}^{K} P_r(q) \delta(r)}{R} \), where \( R \) is the number of retrieved items and \( P_r(q) \delta(r) \) is the precision at position \( r \) for query \( q \). \( \delta(r) \) is set to 1 if the \( r^{th} \) retrieved item has the same label or shares at least one label with query \( q \), else it is set to 0. For comparison against the standard cross-modal techniques, the proposed approach is evaluated using two performance metrics, namely, normalized discounted cumulative gain C@K and Precision P@K [20]. P@K corresponds to the number of relevant results in the first K retrieved data, but do not give emphasis on the rank order within the top-K items. C@K uses graded (instead of binary) relevance and puts more emphasis on the rank order of the correctly retrieved items within the top-K results. We denote the proposed generalized semantic preserving hashing approach as GSPH from now.

B. Analysis of different versions of the algorithm

First, we analyze the different versions of the proposed algorithm using KLR in Stage 2 on the Wikipedia dataset. As expected, the quantitative results in terms of MAP are found to be similar for all the algorithms. The running time of the algorithm (Stage 1) for 100 iterations in seconds is provided in Table I. Here the notations are (1) Algo 1: algorithm proposed in [17], (2) Algo 2: column update version, (3) Algo 3: matrix update version, (4) Algo 4: column update version solved with the discrete constraints (as in [25]). The system configuration used is Intel Core i7-3770 CPU @ 3.40 GHz 32 GB RAM. We observe that Stage 1 takes considerably lesser time using the matrix update as compared to element-wise or column-wise update. Thus, we have used Algo 3 for all the remaining experiments in this work.

C. Single Label-Paired (SL-P) Evaluation

Here, we evaluate the retrieval performance of the proposed approach on the single-labeled Wiki dataset [21]. Comparisons with the state-of-the-art hashing techniques developed specifically for this scenario is given in Table II. Since this evaluation protocol has paired setting, the results of the proposed algorithm is obtained using the unified hash code. Following the same protocol as in [15], while learning the hash function using KLR, we utilize both random sampling \((klr+r)\) and k-means clustering \((klr+k)\) and report both the results. The results using linear regression are reported as \((k + lin)\). We compare with both state-of-the-art supervised approaches, namely CMSSH [3], CVH [13], KSH-CV [37], SCM [31],
TABLE I

<table>
<thead>
<tr>
<th>Timing (in secs.)</th>
<th>16</th>
<th>32</th>
<th>64</th>
<th>128</th>
</tr>
</thead>
<tbody>
<tr>
<td>Algo 1</td>
<td>190.38</td>
<td>371.70</td>
<td>708.86</td>
<td>1402.04</td>
</tr>
<tr>
<td>Algo 2</td>
<td>131.55</td>
<td>260.43</td>
<td>507.86</td>
<td>1030.72</td>
</tr>
<tr>
<td>Algo 3</td>
<td>8.83</td>
<td>9.76</td>
<td>11.92</td>
<td>15.78</td>
</tr>
<tr>
<td>Algo 4</td>
<td>175.89</td>
<td>334.08</td>
<td>647.34</td>
<td>1259.74</td>
</tr>
</tbody>
</table>

TABLE II

MAP COMPARISON OF GSPH WITH STATE-OF-THE-ART ON WIKI [21] FOR SL-P WITH DIFFERENT HASH CODE LENGTHS

<table>
<thead>
<tr>
<th>Image-to-Text</th>
<th>Text-to-Image</th>
</tr>
</thead>
<tbody>
<tr>
<td>q=16</td>
<td>q=32</td>
</tr>
<tr>
<td>CMSSH&lt;sup&gt;1&lt;/sup&gt;</td>
<td>0.187</td>
</tr>
<tr>
<td>CVH&lt;sup&gt;2&lt;/sup&gt;</td>
<td>0.125</td>
</tr>
<tr>
<td>IMH&lt;sup&gt;3&lt;/sup&gt;</td>
<td>0.157</td>
</tr>
<tr>
<td>LSSH&lt;sup&gt;4&lt;/sup&gt;</td>
<td>0.214</td>
</tr>
<tr>
<td>CMFH&lt;sup&gt;5&lt;/sup&gt;</td>
<td>0.213</td>
</tr>
<tr>
<td>KSH-CV&lt;sup&gt;6&lt;/sup&gt;</td>
<td>0.196</td>
</tr>
<tr>
<td>SCM_Orth&lt;sup&gt;5&lt;/sup&gt;</td>
<td>0.159</td>
</tr>
<tr>
<td>SCM_Seq&lt;sup&gt;6&lt;/sup&gt;</td>
<td>0.221</td>
</tr>
<tr>
<td>SePH&lt;sub&gt;klr+k&lt;/sub&gt;</td>
<td>0.284</td>
</tr>
<tr>
<td>GSPH&lt;sub&gt;k&lt;/sub&gt;</td>
<td>0.281</td>
</tr>
<tr>
<td>GSPH&lt;sub&gt;klr+k&lt;/sub&gt;</td>
<td>0.292</td>
</tr>
<tr>
<td>GSPH&lt;sub&gt;klr+k&lt;/sub&gt;</td>
<td>0.290</td>
</tr>
</tbody>
</table>

D. Multi Label-Paired (ML-P) Evaluation

For the ML-P scenario, we evaluate the proposed approach on four different datasets, MirFlickr [9], NUS-WIDE [4], LabelMe [23] and Pascal [6]. Table III shows the performance of the proposed approach on the MirFlickr [9] dataset using MAP as the evaluation metric. As the training data is paired, we use the unified hash code as in [15]. Following the same protocol as in [15], we consider 5000 image-text samples during training. The results of all the other approaches have been taken directly from the respective papers. We observe that GSPH<sup>1</sup> performs favorably compared to the state-of-the-art approaches. We also observe that without regenerating the hash codes, the performance of GSPH<sup>2</sup> is significantly better compared to DCH<sup>2</sup>.

We also evaluate GSPH<sub>klr+k</sub> by increasing the number of training samples and the number of kernel samples in the second stage. We observe from Fig. 2(a) and 2(b) that the MAP increases consistently with both. For example, we obtain MAP of 0.705 and 0.769 with 128 bit and 2000 samples in KLR. The performance can be increased further if the full training set is utilized.

Table IV shows the performance of the proposed approach on the NUS-WIDE [4] dataset using MAP@50 as the evaluation metric. As in [15], we use the unified hash code, 5000 training samples and the unification strategy described earlier. For this data, we use the evaluation protocol in [34] so that we can compare with the recent, very popular quantization approaches (though it works in an unsupervised setting). The results of the other approaches have been taken directly from [34]. We repeat the experiments of SePH [15] following the same protocol as in [34]. We observe that the proposed approach, in general, outperforms both the state-of-the-art supervised as well as the unsupervised approaches. For this data also, we observe that the performance of GSPH<sub>klr+k</sub> is significantly better compared to DCH<sup>2</sup>.

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increases significantly with the increase in the number of training samples and kernel samples in Stage 2. For example, we obtain MAP of 0.663 and 0.827 with 128 bit and 3500 samples in KLR (with the training size fixed) and MAP of 0.685 and 0.833 with 128 bit and 20,000 training samples (with 500 kernel samples in KLR).

Evaluation on Unseen Test Data: For evaluating the hashing techniques, usually the training set consisting of both the image and text data is used as the database from which data is retrieved during testing, while the query is an unknown text or image. There is also another evaluation criteria where the testing data is completely unseen during training, which allows us to evaluate the generalizability of the approaches for unseen data. Thus, in addition to the above experiments, we perform two additional experiments using this setting on the Pascal [6] and LabelMe [23] datasets, which are both multi-label and compare with some state-of-the-art algorithms.

In this setting, unified hash codes cannot be used for retrieval since, during testing, both the query and the database consists of data from a single modality. For both the datasets, the results of the proposed approach using Bow, Color, and Gist features are given in Table V and Table VI. Comparison with CCA [8], cluster-CCA [22], 3-view CCA [7] and FCCA [20] for both text-to-image and image-to-text cross-modal tasks are also reported. The results of the other approaches are directly taken from [20]. For both these tasks, the relevance of any retrieved object is decided based on the similarity between the labels of the query and retrieved item and C@30 and P@10 are used as the performance measures. For the LabelMe [23] dataset, we follow the same procedure as in [20] for extracting the CNN features [12]. We could not replicate the performance using the CNN features on the Pascal dataset for the baseline algorithms, and so we do not report its performance. We also compare with the state-of-the-art supervised hashing technique SePH [15] for this protocol using the code provided by the authors. We experimented with different parameters for SePH and report the best results here. The best results for the LabelMe dataset [23] are obtained with the whole training set to construct the hash codes and learn the hash functions. Thus, we see the proposed approach works seamlessly for both the SL-P and ML-P scenarios.

E. Unpaired Scenario (SL-U, ML-U) Evaluation

We now report the results of the proposed approach for unpaired scenarios, both for single and multi-label data (SL-U and ML-U). For the SL-U case, each data point is associated with a single label but there does not exist a one-to-one correspondence between the data of the two modalities. For evaluation, we create the SL-U scenario by slightly modifying the training protocol for the Wiki [21] dataset. The training set in one modality is kept the same while in the other modality, a variable percentage of it is retained. In our experiments, we have retained the full-text domain data and taken a percentage of the image domain data (Table VII-VIII). We have also conducted experiments in the opposite setting i.e., by retaining a percentage of the text domain data and observed similar results. Here, we use the 693 pairs of the testing set as the probe and gallery. As the training and testing splits are different, we re-generate the hash codes again. We compare the proposed method against CCA [8] and SePH [15], FCCA [20], and CCA has been specifically developed to handle this scenario, and FCCA [20] reduces to CCCA in this situation. For implementing CCA [8] and SePH [15], we artificially construct paired training sets for learning the projection matrices. We also adapt the SCM algorithm [31] for the unpaired scenario by replacing $\tilde{S} = \tilde{L}_x \tilde{L}_y^T$ with $\tilde{S} = \tilde{L}_x \tilde{L}_y$, where $\tilde{L}_x, \tilde{L}_y$ denotes the labels of the two modalities. We observe from Table VII, that the
proposed approach performs favorably compared to the other approaches.

We also generate a similar scenario for the multi-label case (ML-U) using the LabelMe [23] dataset. We use the Gist features for image representation. We use the whole training data in one modality and retain a variable percentage from the other modality to create the training set. The testing sets remain the same as in ML-P case. We compare our approach with CCA [8] and FCCA [20] using P@10. For CCA [8] and SePH [15] implementation, we construct paired sets as before. The results in Table VIII show superior performance of the proposed algorithm over the other baselines.

F. Handling large amounts of data/ Online training

We have seen that the proposed algorithm with matrix update is quite fast and can handle large training data size. Nevertheless, there may be cases, where the training data is too large to be handled by even the proposed approach since the size of the affinity matrix will be very large. Also, the training data may not be available at the same time, like in online training, where the training data may be available in batches. Here, we propose an iterative approach for these scenarios.

We denote the data available initially (in online training scenario) in the two modalities as $X_f \in \mathbb{R}^{n_f \times d_x}$ and $Y_f \in \mathbb{R}^{n_f \times d_y}$. Here, $n_f$ is the number of training samples, and $d_x$, $d_y$ are the feature dimensions in the two modalities. The affinity matrix for this fixed batch of data is $S_f$. Using the affinity matrix, we use the proposed approach to generate the hash codes, $A_f$ and $B_f$. Suppose, now we get a batch of $n_i$ training data, denoted by $X_i \in \mathbb{R}^{n_i \times d_x}$ and $Y_i \in \mathbb{R}^{n_i \times d_y}$. If the hash codes for this data is generated independently, they may not satisfy the affinity relationships with the existing data given by $S_f$. We concatenate the data to form $\hat{X} = [X_f \; X_i]$ and $\hat{Y} = [Y_f \; Y_i]$. The affinity matrix thus formed is given as
respectively for bit lengths of \( \lambda \) and \( \sigma \) respectively. We use the radial basis function kernel, and some implementation details. For learning the hash functions, none of the competing algorithms can handle exponential function (\( e^x \)) using KLR for different unification strategies. We obtain MAP and MirFlickr [9] dataset respectively. We did not observe step for linear ridge regression is 500 and 1000 for Wiki [21] and Pascal [6] datasets respectively. The number of anchors in the kernel pre-processing matrix for the LabelMe [23] and Pascal [6] datasets respectively. This is slightly less than what we obtained when we used the whole training data to get the hash codes (GSPH\(_{k, r, k}^2 \) results in Table II and III). This is because here all the relations may not be maintained strictly since the relations between the different batches is only through the fixed batch. For NUS-WIDE dataset (with \( P = 5000, mb = 5000 \)), we get the the performance for the different bits as [0.763, 0.737, 0.771, 0.775] and [0.867, 0.881, 0.886, 0.891] respectively for bit lengths of \{16, 32, 64, 128\}. To the best of our knowledge, none of the competing algorithms can handle all the training samples of a dataset as large as NUS-WIDE.

G. Analysis and Implementation details

Here we present some analysis of the proposed approach and some implementation details. For learning the hash functions using KLR, we use the radial basis function kernel, the numbers of samples were taken as 500 and the regularization parameter \( \lambda = 0.01 \). We use the inner product and the exponential function (\( e^x \)) for construction of the affinity matrix for the LabelMe [23] and Pascal [6] datasets respectively. The number of anchors in the kernel pre-processing step for linear ridge regression is 500 and 1000 for Wiki [21] and MirFlickr [9] dataset respectively. We did not observe significant improvement for the NUS-WIDE dataset and thus did not use kernel pre-processing.

We also evaluate the proposed approach with 128 bits using KLR for different unification strategies. We obtain MAP of \{0.2931, 0.3057, 0.33249\}, \{0.4710, 0.6739, 0.6815\} for Wiki [21] and \{0.5908, 0.5943, 0.6457\}, \{0.6623, 0.7557, 0.7939\} for NUS-WIDE [4] respectively, thus justifying the effectiveness of the proposed unification.

Now, we analyze the performance of the proposed approach with SePH [15], which are conceptually similar. The retrieval performance of both algorithms depends on how well the learned hash codes capture the semantic relationships and on how well the learned hash functions can map the input features to the hash codes. Table IX compares the performance of the algorithms on the training set of LabelMe [23] data. Stage 1 denotes the scenario where the learned hash codes are directly used for retrieval and Stage 2 denotes the scenario where the learned hash functions are used to regenerate the hash codes. We observe that for both the stages, the proposed algorithm outperforms SePH [15], indicating that the proposed algorithm is able to generate better hash codes and hash functions.

In the proposed approach, since learning the hash function is separate from learning the hash codes, more recent and sophisticated techniques can be used in Stage 2 to learn more complicated hash functions, which makes the approach more flexible. We also observe that when the learned hash codes are used for retrieval instead of the regenerated ones, the performance is better (both for DCH [30] and GSPH\(^2 \)), since the hash functions may not be able to learn the exact mapping. In this scenario, the proposed approach performs significantly better than DCH [30], which may be because the affinity matrix encodes all the relationships between the data instead of just pairwise correspondences.

Now we compare our algorithm with a recently proposed end-to-end deep cross-modal hashing technique DCMH [11]. The paradigm of DCMH [11] is similar to ours with some

![Table IX](image)

**Table IX**

<table>
<thead>
<tr>
<th>Task</th>
<th>Method</th>
<th>MIRFLICKR-25K</th>
<th>IAPR TC-12</th>
<th>NUS-WIDE</th>
</tr>
</thead>
<tbody>
<tr>
<td>( I \rightarrow T )</td>
<td>DCMH</td>
<td>0.79</td>
<td>0.79</td>
<td>0.79</td>
</tr>
<tr>
<td></td>
<td>GSPH(_{k, r, k}^2) (a)</td>
<td>0.74</td>
<td>0.75</td>
<td>0.75</td>
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<tr>
<td></td>
<td>GSPH(_{k, r, k}^2) (b)</td>
<td>0.75</td>
<td>0.76</td>
<td>0.76</td>
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<tr>
<td></td>
<td>GSPH(_{k, r, k}^2) (c)</td>
<td>0.76</td>
<td>0.78</td>
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<tr>
<td></td>
<td>GSPH(_{k, r, k}^2) (d)</td>
<td>0.85</td>
<td>0.86</td>
<td>0.86</td>
</tr>
</tbody>
</table>

![Table X](image)

**Table X**

<table>
<thead>
<tr>
<th>Task</th>
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<th>MIRFLICKR-25K</th>
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<tr>
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<td>GSPH(_{k, r, k}^2) (b)</td>
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<tr>
<td></td>
<td>GSPH(_{k, r, k}^2) (c)</td>
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<td>0.78</td>
<td>0.78</td>
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<tr>
<td></td>
<td>GSPH(_{k, r, k}^2) (d)</td>
<td>0.85</td>
<td>0.86</td>
<td>0.86</td>
</tr>
</tbody>
</table>

**unification strategy presented in this work.** We also obtain MAP of \{0.2931, 0.3057, 0.33249\}, \{0.4710, 0.6739, 0.6815\} for Wiki [21] and \{0.5908, 0.5943, 0.6457\}, \{0.6623, 0.7557, 0.7939\} for NUS-WIDE [4] respectively, thus justifying the effectiveness of the proposed unification.

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notable differences - (1) DCMH uses either [1, 0] to construct the affinity matrix $S$ for both SL and ML datasets. In contrast, GSPH uses inner product which takes into account the non-binary similarity in case of ML datasets; (2) GSPH has a unification strategy to generate common hash codes, which in general gives considerable improvement in performance; (3) The iterative scheme enables GSPH to handle large amounts of training data without explicitly forming and storing large affinity matrix $S$. This enables us to use the already generated hash codes which give better performance compared to the re-generated ones. Table X compares the performance of GSPH with DCMH [11] for the three datasets using the same protocol as in [11]. The notations in Table X {$(a), (b), (c)$} denote no unification, unification as in [17] and using the new strategy.

V. CONCLUSION

In this work, we proposed a generalized hashing approach for cross-modal retrieval. The approach can work in different settings like single label, multi-label, and both paired and unpaired scenario while preserving the semantic similarity between data points. In the first stage, we optimize a non-convex problem by using alternating minimization to learn the hash codes for different modalities. The hash functions are learned in the second stage, and recent sophisticated techniques can also be used seamlessly for this part to learn complicated hash functions. The learned hash codes can be further unified if paired data is available. We have also proposed an iterative approach which enables us to learn hash codes for huge amounts of training data or for online training scenario. Extensive experiments on several datasets show the effectiveness of the proposed approach for different scenarios.

REFERENCES


