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To Show the Multiple Alignment of the Image search Hash Efficiency

[1] Mr. D. Venkatarami Reddy,[2] Mr. Narasimha Rao, [3] Mr. S. Naveen
[1]Associate Professor &HOD, ECE, Madhira Institute of Technology & science, Chilkur, Suryapet, India
[2]Assistant Professor in ECE, Madhira Institute of Technology & science, Chilkur, Suryapet, India
[3]PG Scholar, ECE, Madhira Institute of Technology & science, Chilkur, Suryapet, India
[1]dvenkataramireddy@gmail.com,[2]Jwala.ronaldo@gmail.com,[3]naveen.sirapurapu007@gmail.com

ABSTRACT

Hashing is a popular and efficient method for nearest neighbor search in large-scale data spaces, by embedding high-dimensional feature descriptors into a similarity-preserving Hamming space with a low dimension. For most hashing methods, the performance of retrieval heavily depends on the choice of the high-dimensional feature descriptor. Furthermore, a single type of feature cannot be descriptive enough for different images when it is used for hashing. Thus, how to combine multiple representations for learning effective hashing functions is an imminent task. In this paper, we present a novel unsupervisedMultiview Alignment Hashing (MAH) approach based on Regularized Kernel Nonnegative Matrix Factorization (RKNMF), which can find a compact representation uncovering the hidden semantics and simultaneously respecting the joint probability distribution of data. Specifically, we aim to seek a matrix factorization to effectively fuse the multiple information sources meanwhile discarding the feature redundancy. Since the raised problem is regarded as nonconvex and discrete, our objective function is then optimized via an alternate way with relaxation and converges to a locally optimal solution. After finding the Low-dimensional representation, the hashing functions are finally obtained through multivariable logistic regression. The proposed method is systematically evaluated on three datasets: Caltech-and the results show that our method significantly outperforms the state-of-the-art multiviewhashing techniques.

I. INTRODUCTION

LEARNING discriminative embedding has been a critical problem in many fields of information processing and analysis, such as object recognition image/video retrieval and visual detection Among them, scalable retrieval of similar visual information is attractive, since with the advances of computer technologies and the development of the World Wide Web, a huge amount of digital data has been generated and applied. The most basic but essential scheme for similarity search is the nearest neighbor (NN) search: given query image, to find an image that is most similar to it within large database and assign the same label of the nearest neighbor to this query image. NN search is regarded as a linear search scheme (O (N)), which is not scalable due to the large sample size in datasets of practical applications. Later, to overcome this kind of computational complexity problem, some tree-based search schemes are proposed to partition the data space via various tree structures. Among them, KD-tree and R-tree [6] are successfully applied to index the data for fast query responses. However, these methods cannot operate with

High-dimensional data and do not guarantee faster search compared to the linear scan. In fact, most of the vision-based tasks suffer from the curse of dimensionality problems1, because visual descriptors usually have hundreds or even thousands of dimensions. Thus, some hashing schemes are proposed to effectively embed data from a high-dimensional feature space into a similarity-preserving low-dimensional Hamming space where an approximate nearest neighbor of a given query can be found with sub-linear time complexity. One of the most well-known hashing techniques that preserve similarity information is Locality-Sensitive Hashing (LSH) [7]. LSH simply employs random linear projections (followed by random thresholding) to map data points close in a Euclidean space to similar codes. Spectral Hashing (Ph.) [8] is a representative unsupervised hashing method, in which the Laplace-Beltrami Eigen functions of manifolds aroused to determine binary codes. Moreover, principled linear projections like PCA Hashing (PCAH) [9] has been suggested for better quantization rather than random projection hashing.

Besides, another popular hashing approach, Anchor Graphs Hashing (AGH) [10], is proposed to learn compact binary codes via tractable low-rank adjacency matrices. AGH allows constant time hashing of a new data point by extrapolating graph Laplacian eigenvectors to Eigen functions. More relevant hashing methods can be however, single-view hashing is the main topic on which the previous exploration of hashing methods focuses. In their architectures, only one type of feature descriptor is used for learning hashing functions. In practice, to make a more comprehensive description, objects/images are always representedvia several different kinds of features and each of them has its own characteristics. Thus, it is desirable to incorporate

These heterogeneous feature descriptors into learning hashing functions, leading to multi-view hashing approaches. Multiviewlearning techniques have been well explored in the past few years and widely applied to visual information fusion. Recently, a number ofmultiview hashing methods have been proposed for efficient similarity search, such as Multi-View Anchor Graph Hashing(MVAGH) [21], Sequential Update for Multi-View Spectral Hashing (SU-MVSH) [22], Multi-View Hashing (MVH-CS)1The effectiveness and efficiency of these methods drop exponentially as the dimensionality increases, which is commonly referred to as the curse of

Dimensionality Composite Hashing with Multiple Information Sources (CHMIS) [24] and Deep Multi-view Hashing (DMVH) [25].These methods mainly depend on spectral, graph or deep learning techniques to achieve data structure preserving encoding. Nevertheless, the hashing purely with the above schemes

Are usually sensitive to data noise and suffering from the high computational complexity. The above drawbacks of prior work motivate us to propose novel unsupervised mulitiview hashing approach, termed MultiviewAlignment Hashing (MAH), which can effectively fuse multiple information sources and exploit the discriminative low-dimensional embedding via Nonnegative Matrix Factorization (NMF). NMF is a popular method in data mining tasks including clustering, collaborative filtering, outlier detection, etc. Unlike other embedding methods with positive and negative values, NMF seeks to learn a nonnegative partsbasedrepresentation that gives better visual interpretation of factoring matrices for high-dimensional data. Therefore, in many cases, NMF may be more suitable for subspace learning tasks, because it provides a non-global basis set which intuitively contains the localized parts of objects [26].In addition, since the flexibility of matrix factorization can handle widely varying data distributions, NMF enables more robust subspace learning. More importantly, NMF decomposes an original matrix into a part-based representation that gives better interpretation of factoring matrices for non-negative data.

When applying NMF to multitier fusion tasks, a partbasedrepresentation can reduce the corruption between any two views and gain more discriminative codes. To the best of our knowledge, this is the first work usingNMF to combine multiple views for image hashing. It is

worthwhile to highlight several contributions of the proposed method:_ MAH can find a compact representation uncovering the hidden semantics from different view aspects and simultaneously respecting the joint probability distribution of data._ To solve our nonconvex objective function, a new alternate optimization has been proposed to get the final

Solution. We utilize multivariable logistic regression to generate the hashing function and achieve the out-of-sample extension.

II. A BRIEF REVIEW OF NMF

In this section, we mainly review some related algorithms, focusing on Nonnegative Matrix Factorization (NMF) and its variants. NMF is proposed to learn the nonnegative parts of objects. Given a nonnegative data matrix X = [x1; _ _ _; Xin] 2RD_N_0, each column of X is a sample data. NMF aims to find two nonnegative matrices U 2 RD_d_0 and V 2 Rd_N_0with full rank whose product can approximately represent the original matrix X, i.e., X _ UV. In practice, we always have <min (D; N). Thus, we minimize the following objectivefunctionLNMF = Ki UV K2; stud; V _ 0; (1) where kaki is Fresenius norm. To optimize the above objective

Function, an iterative updating procedure was developed in It has been proved that the above updating procedure can find the local minimum of LNMF. The matrix V obtained in NM is always regarded as the low-dimensional representation while the matrix U denotes the basis matrix. Furthermore, there also exists some variants of NMF. LocalNMF (LNMF) [27] imposes a spatial localized constraint on the bases. In [28], sparse NMF was proposed and later, NMF constrained with neighborhood preserving regularization (NPNMF) [29] was developed. Besides, researchers also proposed graph regularized NMF (GNMF) [30], which effectively preserves the locality structure of data. Beyond these methods, extends the original NMF with the kernel trick as kernelizedNMF (KNMF), which could extract more useful features hidden in the original data through some kernel-induced nonlinear mappings. Moreover, it can deal with data where only relationships (similarities or dissimilarities) between objects are known. Specifically, in their work, they addressed the matrix factorization by K _ UV, where K is the kernel matrix instead of the data matrix X, and (U; V) are similar with standard NMF. More related to our work, a multiple kernels NMF (MKNMF) [32] approach was proposed, where linear programming is applied to determine the combination of different kernels.

In this paper, we present a Regularized Kernel Nonnegative Matrix Factorization (RKNMF) framework for hashing, which can effectively preserve the data intrinsic probability distribution and simultaneously reduce the redundancy of lowdimensionalrepresentations. Rather than locality-based graph regularization, we measure the joint probability of pairwise data by the Gaussian function, which is defined over all the potential neighbors and has been proved to effectively resist data noise. This kind of measurement is capable to capture the local structure of the high-dimensional data while also revealing global structure such as the presence of clusters at

Several scales. To the best of our knowledge, this is the first time that NMF with multitier hashing has been successfully applied to feature embedding for large-scale similarity search.

III. MULTIVIEW ALIGNMENT HASHING

In the section, we introduce our new Multitier Alignment Hashing approach, referred as MAH. Our goal is to learn awash embedding function, which fuses the various alignment representations from multiple sources while preserving the high-dimensional joint distribution and obtaining the orthogonalbases simultaneously during the RKNMF. Originally, we need to find the binary solution which, however, is first relaxed to a real-valued range so that a more suitable solution can be gained. After applying the alternate optimization, we convert

The real-valued solutions into binary codes

Algorithm 1 Multiview Alignment Hashing (MAH)

Input: A set of training kernel matrices from n different views: $\{K_1, \cdots, K_n\}$ computed via *Heat Kernel*; the objective dimension of hash code d; learning rate r for logistic regression and regularization parameters $\{\gamma, \eta, \xi\}$.

Output: Kernel weights $\alpha = (\alpha_1, \cdots, \alpha_n)$, basis matrix U and regression matrix Θ.

1: Calculate matrix $W^{(i)}$ for each view through Eq. (5);
2: Initialize $\alpha = (1/n, 1/n, \cdots, 1/n)$;
3: **repeat**
4: Compute the basis matrix U and the low-dimensional representation matrix V via Eq. (11) and Eq. (12);
5: Obtain kernel weights $\alpha^T = \widetilde{A}^{-1}\widetilde{B}$ with Eq. (20);
6: **until** convergence
7: Calculate the regression matrix Θ by Eq. (22) and the final MAH encoding for a sample is defined in Eq. (23).

IV. EXPERIMENTS AND RESULTS

In this section, the MAH algorithm is evaluated for the high dimensional nearest neighbor search problem. Three different datasets are used in our experiments, i.e., Caltech-256 [44], CIFAR-10 [45] and CIFAR-20 [45]. Caltech-256 consists of30607 images associated with 256 object categories. CIFAR-10 and CIFAR-20 are both 60; 000-image subsets collected from the 80-million tiny images dataset [46] with 10 class labels and 20 class labels, respectively. Following the experimental setting in for each dataset, we randomly select 1000 images as the query set and the rest of datasets used as the training set. Given an image, we would like to describe it with multitier features extracted from it. The descriptors are expected to capture the orientation, intensity, texture and color information, which are the main cues of animate. Therefore, 512-dim Gist3 [47], 1152-dim histogram of oriented gradients (HOG) 4 [48], 256-dim local binary pattern (LBP) 5 [49] and 192-dim color histogram (Colorist) 6 are respectively employed for image representation.3Gabor filters are applied on images with 8 different orientations and 4scales. Each filtered image is then averaged over 4 _ 4 grid leading to a512-dimensional vector (8 _ 4 _ 16 = 512).436 4 _ 4 non-overlapping windows yield a 1152-dimensional vector.5The LBP labels the pixels of an image by thresholding a 3_3 neighborhood, and responses are mapped to a 256-dimensional vector.6For each R,G,B channel, a 64-bin histogram is computed and the total length is 3 _ 64 = 192.In the test phase, a returned point is regarded as a true neighbor if it lies in the top 100, 500 and 500 points closest to query for Caltech-256, CIFAR-10 and CIFAR-20, respectively. For each query, all the data points in the database are ranked according to their Hamming distances to the query, since it is fast enough with short hash codes in practice. We then evaluate the retrieval results by the Mean Average Precision (MAP) and the precision-recall curve. Additionally, we also report the training time and the test time (the average searching time used for each query) for all the methods. All experiments are performed using Mat lab 2013a on a server configured with a12-core processor and 128G of RAM running the Linux OS.

A. Compared Methods and Settings

We compare our method against six popular unsupervisedmultiview hashing algorithms, i.e., Multi-View Anchor Graph Hashing (MVAGH) [21], Sequential Update for

Multi-View Spectral Hashing (SU-MVSH) [22], Multi-View Hashing(MVH-CS) [23], Composite Hashing with Multiple Information Sources (CHMIS) [24], Deep Multi-view Hashing(DMVH) [25] with a 4-layers deep-net and a derived version ofMVH-CS, termed MAV-CCA, which is a special case of MAVCSwhen the averaged similarity matrix is fixed as the identity matrix [23]. MAH-3 represents the original MAH without the orthogonal constraint.)The step of 0:01 which yields the best performance by 10-fold cross-validation on the training data. The choice of three regularization parameters f; _; _g is also done via crossvalidationon the training set and we finally fix = 0:15, _ = 0:325 and _ = 0:05 for all three datasets. To further speedup the convergence of the proposed alternate optimization procedure, in our experiments, we apply a small trick with the following steps:

1) For the first time to calculate U and V in the step of optimizing (U; V) in Section III-B, we

2) From the second time, we optimize (U; V) by using the stored U and V from the last time to initialize the NM algorithm, instead of using random values. This small improvement can effectively reduce the time of convergence in the training phase and the corresponding combinations of similarity probability regularization items Li also follow the above similar schemes. The results on three datasets demonstrate that integrating multiple features achieves better performance than using single features and the proposed weighted combination improves the performance compared with average and product schemes. On three datasets. In its entirety, firstly the retrieval accuracies on the CIFAR-10 dataset are obviously higher than that on the more complicated CIFAR-20 and Caltech-256 datesets.Secondly, the multitier methods always achieve better results than single-view schemes. It is obviously observed that the proposed method has significantly improved the effectiveness of NMF and its variants in terms of accuracies.

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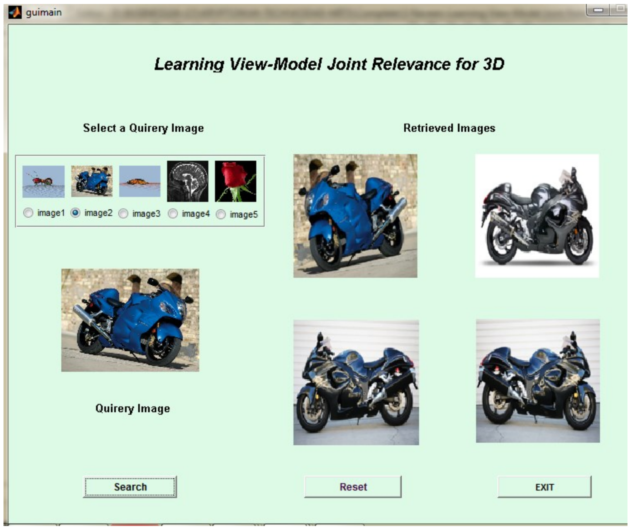

V. CONCLUSION

In this paper, we have presented a novel unsupervised hashing method called Multitier Alignment Hashing (MAH), where hashing functions are effectively learnt via kernelizedNonnegative Matrix Factorization with preserving data joint probability distribution. We incorporate multiple visual features from different views together and an alternate way is introduced to optimize the weights for different views and simultaneously produce the low-dimensional representation. We address this as a nonconvex optimization problem and its alternate procedure will finally converge at the locally optimal solution. For the out-of-sample extension, multivariable logistic regression has been successfully applied to obtain the regression matrix for fast hash encoding. Numerical experiments have been systematically evaluated on Caltech-256, CIFAR-10 and CIFAR-20 datasets. The results manifest that our MAH significantly outperforms the state-of-the-artmultiview hashing techniques in terms of searching accuracies.

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AUTHOR'S PROFILE

Mr.Devireddy Venkatarami Reddy, received the Master of Technology degree in EMBEDDED SYSTEMS from the DR.PAULRAJ ENGINEERING COLLEGE - JNTUH, he received the Bachelor of Engineering degree from S.A. ENGINEERING COLLEGE -ANNA UNIVERSITY. He is currently working as Associate Professor and a Head of the Department of ECE with Madhira Institute of Technology And Sciences, kodad. His interest subjects are Embedded Systems, Microprocessors, Communication Systems, Digital Electronics and etc.
Email id:dvenkataramireddy@gmail.com

Mr. T NARASIMHA RAO, received the Master of Technology degree in ECE from the SANA ENGINEERING COLLEGE-JNTUH, he received the Bachelor of Technology degree from SV ENGINEERING COLLEGE-JNTUH. He is currently working as assistant professor in the Department of ECE with Madhira Institute of Technology And Sciences, kodad. His interest subjects are VLSI, Digital Electronics, Digital Signal Processing and etc.
Email id:jwala.ronaldo@gmail.com

Mr. S.NAVEEN was completed his Beach in Electronics and Communication Engineering at Gandhi Academy of Technical Education, Kodad, Serape, Telangana. Currently he is pursuing his Match in Electronics and Communication Engineering at Madhira institute of technology and sciences, Kodad, Serape, and Telangana. His interests are image and video processing.
Email id: naveen.sirapurapu007@gmail.com