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Cross-Media retrieval using Generative Hashing Methods

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ABSTRACT: Hashing methods are very useful as they can be used for many tasks such as in search engines for cross media retrieval. Here hashing method has been proposed to capture similarities between cross-media information such as textual, visual. As words of different form may have similar meaning. Hence to solve such issues semantic hashing method is used in this paper along with surf++ algorithm. Thus this paper focuses to capture similarity between cross-media data and also on the efficiency of proposed method.

KEYWORDS: Hashing, cross-media, semantic.

I. Introduction

Along with other increasing requirements, social networking has received a big attention these days. Now-a-days digital information is very easy to access , modify and duplicate. As mobile networks and social media sites are elaborating, information input through various channels is possible. Images and videos are entitled with short tags or captions which give rise to a lot of relevant data. This relevant data have semantic correlations. Hence hashing based methods are used. Because of this information retrieval and duplicate detection is possible. Cross-media retrieval is type of retrieval in which the user input query and the obtained results can be of different form. Therefore, it is desirable to support the retrieval of information through different modalities. For example, images can be used to find semantically relevant textual information. On the other side, images without (or with little) textual descriptions are highly needed to be retrieved with textual query.

Most of the existing works use a bag-of-words to model textual information. The semantic level similarities between words or documents are rarely considered. In short text segments (e.g., microblogs , captions, and tags), the similarities between words are especially important for retrieval. Since words with different forms may have similar meaning .For example: journey versus travel, coast versus shore. According to human-assigned similarity judgments more than 90 percent of subjects thought that these pairs of words had similar meanings. Hence, to construct the relation between textual and visual modes[2].

II. Related work

In this process of hashing there are mainly three steps involved input a query , extracting corresponding information using hashing and giving results to the user. Thus various methods are used for retrieval of cross-media till today. They are cross view hashing, Semantic correlation maximization Discriminative coupled dictionary hashing, Latent semantic sparse hashing, Collective matrix hashing[2].S. Kumar and R. Udupa proposed Cross-view Hashing which maps similar objects to similar codes across the views to enable similarity search. In this work, a hashing-based approach for solving the cross-view similarity search problem is used where each view of a multi-view data object as a compact binary codeword is represented. To support this similarity search, we need the code words of a data object to be similar if not identical. Later, code words of similar data objects should also be similar[1]. Assuming that we can somehow map data objects to binary code-words, cross-view similarity search can be reduced to the much simpler problem of retrieving all data objects using hamming distance code word, the codeword for the query.Discriminative coupled

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dictionary hashing generates a coupled dictionary for each modality based on category labels. In this paper[9], they introduced a discriminative coupled dictionary hashing approach, coupled dictionary for each modality based on category labels which helped in fast cross-media retrieval. Multi view discriminative coupled dictionary hashing(MV-DCDH) is extended from DCDH with multi-view representation to enhance the representing capability of the relatively "weak" modalities[2].Latent semantic sparse hashing uses Matrix Factorization J. Zhou, G. Ding, and Y. Guo , proposed the use of Factorization to represent text and sparse coding to capture the salient structures of images. LSSH requires the use of both visual and textual information to construct the data set[8]. In this paper[4]Collective matrix factorization hashing (CMFH) generates unified hash codes for different modalities of one instance through collective matrix factorization with latent factor model collective matrix factorization. Also Yue Ting Zhuang, found Semantic correlation maximization (SCM) integrates semantic labels into the hashing learning procedure for preserving the semantic similarity cross modalities.H. Zhang, J. Yuan, X. Gao and Z. Chen introduced cross media retrieval Boosting via feature analysis and relevance feedback[10]. This feature analysis is visual-auditory analysis which adds the boosting in retrieval. And in paper[11] it has been explained about Harmonizing hierarchical manifolds for multimedia document semantics understanding and cross-media retrieval[11].In this paper[12]Tri-space and ranking based method which is heterogeneous similarity measure for cross-media retrieval,While other existing methods only focus on the original low level feature spaces or the third common space, their proposed tri-space method focuses on all features.Xiaohua Zhai ,Yuxin Peng ,Jianguo Xiao, Learning Cross-Media Joint Representation With Sparse and Semisupervised Regularization, here to measure the content similarity among different media is the key challenge. In this paper, they propose a novel feature learning algorithm for cross-media data, called joint representation learning (JRL), which is able to explore jointly the correlation and semantic information in a unified optimization framework. JRL integrates the sparse and semisupervised regularization for In this different media types into one unified optimization problem, while existing feature learning methods generally focus on a single media type. On one hand, JRL learns sparse projection matrix for different media simultaneously, so different media can align with each other. Also both the labeled data and unlabeled data of different media types are explored. The Unlabeled data of different media increase the diversity of training data and boost the performance of joint representation learning. Furthermore, JRL incorporate the cross-media correlation into the final presentation[13].In this paper[14] cluster-based correlation analysis (CBCA) to exploit the relation between different types of multimedia objects, and to measure semantic similarities. Based on a collection of documents that are multi-media CBCA first perform clustering on uni-media feature spaces to produce several semantic clusters for each modality. After that, by using the co-occurrence information of semantic clusters of different modalities, CBCA constructs a cross-modal cluster graph (CMCG) to represent the similarities between clusters.Yuxin Peng, Xiaohua Zhai, Yunzhen Zhao, Xin Huang, In this paper, they focus on how to learn cross-media features for different media types is a key challenge. Actually, the data from different media types with the same semantic category are complementary to each other, and jointly modeling them is able to improve the accuracy of cross-media retrieval. In addition, although the labeled data are accurate, they require a lot of human labor and thus are very scarce. To solve such issues a semi-supervised cross-media feature learning algorithm with unified patch graph regularization (S2UPG)[15].Heterogeneous Feature Augmentation (HFA), In this paper, they utilize a new domain adaptation to solve Heterogeneous domain adaptation (HDA) problem in cross-media retrieval using Heterogeneous Feature Augmentation (HFA). First, different dimensions of features are transformed into a common subspace by learning an intermediate variable, and augmented the transformed data with their original features and ones; second, in retrieval stage, we compute the similarity and rank the query results by bag-based re-ranking method[16].Wenchen Cheng; Jiang Qian, Zhicheng Zhao, Fei Su, found large scale cross-media data retrieval based on Hadoop is proposed to speed up the retrieval in this paper. they divide cross-media feature extraction and cross-media retrieval into paralleled pipeline. To verify the performance of the proposed method, comparisons with stand-alone mode on different sizes of the image dataset are conducted.

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III. PROPOSED ALGORITHM

SURF++ algorithm is implemented here. This algorithm is the extention of original algorithm surf. Given a collection of text-image bi-modality data, we will firstly represent image and text respectively. Through table lookup, all the words in a text are transformed and need to extract image Keypoints for representing Images. After these steps, a variable size set of points represents the text, and a variable size set of points represents each image with fixed length. Finally, the mapping functions between textual and visual) are learned by a deep neural network. We will use the learned mapping function to convert one modality to another. Hash code generation methods will be used to transfer different modalities. Following are the sequence of steps:

1. Hash code Generation
2. Matching

Step 1: Various hashing methods are used to create compact hash codes for cross-media retrieval which preserves similarity. In this project , we will use semantic hashing which will create hash codes for the information , information may be visual or textual. Thus hash code generation will be used to transfer different modalities.
Here SURF+ algorithm is used for detection and description scheme. It is partly inspired by Sift descriptor. For representing images , Surf++ detector is used to Extract image keypoints. These extracted keypoints descriptors will be calculated using Surf++ descriptor. Thus a set of points will represent text and one set of points will represent images.

Step 2: By comparing the descriptors obtained from different images, matching pairs can be found**.** For each descriptor, find a match and then verify matches.

IV. SIMULATION RESULTS

In the proposed retrieval of image there are five stages as shown in Fig.1. The proposed surf+ algorithm is implemented here. When a user will query image or text, extraction of image and text takes place. After extraction mapping of image to text and text to image will be carried out and then hash code will be generated. Thus a specific code will be generated for a particular image.

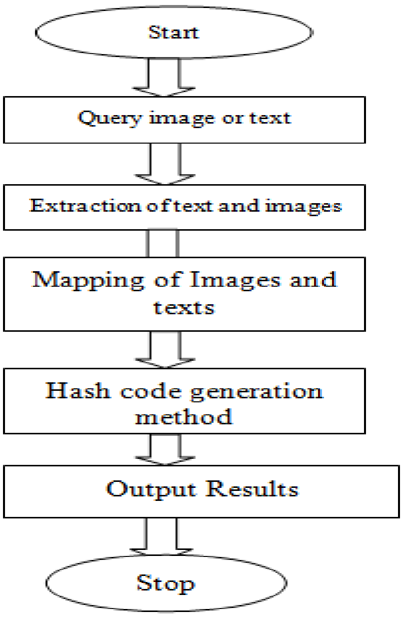

Fig.1. Flow chart for cross media retrieval

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V. CONCLUSION AND FUTURE WORK

Thus for cross-media retrieval we will propose a hashing method which will not confuse images, also will be a fast media retrieval but will not give many similar images. Thus for a better efficiency results will be obtained using less number of iterations which will consume less time as compared to other methods.

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