ISSN: 2455-2631 © September 2017 IJSDR | Volume 2, Issue 9

A Novel Approach for Distance Metric Learning for Multi-Modal Image Retrieval

M .Vinuthna[1], CH. Ratna jyothi[2], A. Yuva krishna[3]

[1]M.tech (CSE), [2]Assistant Professor, [3]Assistant Professor
Dept of CSE
Prasad V Potluri Siddhartha Institute of Technology, Kanuru, Vijayawada, A.P, India

Abstract— **One of the core research problems in multimedia retrieval is to seek an effective distance metric/function for computing similarity of two objects in content-based multimedia retrieval tasks. Distance metric learning (DML) is an important technique to improve similarity search in content-based image retrieval. The paper proposes the current online multi-modal distance metric learning (OMDML) with another component of expansion to illuminate the Image equivocalness issue utilizing fundamental expectation of proposing this model of framework is to comment on/label the images with some physically characterized ideas for learning a natural space, utilizing visual and logical features. All the most especially, by creating the framework to sustain the dormant vectors into existing classification portrayals, it can be authorize to be used of image comment, which is considered as the required issue in image recovery. As an expansion to the accessible model, we suggest and include the substance highlight of the issue of understanding the vagueness. Online multi-modal distance metric learning framework gives a superior results of substance based image recovery show. We investigate a completely unique theme of on-line multi-modal distance metric learning (OMDML), that explores a unified two-level on-line learning scheme: (i) it learns to optimize a distance metric on every individual feature space; and (ii) then it learns to And the optimal combination of diverse types of features. To further reduce the expensive cost of DML on high-dimensional feature space, we propose a low-rank OMDML algorithm which not only significantly reduces the computational cost but also retains highly competing or even better learning accuracy.**

IndexTerms— **Multi-Modal Retrieval, Distance Metric Learning (DML), online multi-modal distance metric learning (OMDML).**

I. Introduction (Heading 1)

A good distance metric/function remains an open challenge for content-based multi-media retrieval tasks till now. In recent years, one promising direction to address this challenge is to explore distance metric learning (DML) by applying machine learning techniques to optimize distance metrics from training data or side information, like historical logs of user relevance feedback in content-based image retrieval (CBIR) systems. Although various DML algorithms have been proposed in literature most existing DML methods in general belong to single-modal DML in that they learn a distance metric either on a single type of feature or on a combined feature space by simply concatenating various types of several features together. In a real-world application, such approaches may suffer from some practical limitations: (i) some types of features may significantly dominate the others with in the DML task, weakening the ability to do the possible of all features; and (ii) the naive concatenation approach may result in a combined high- dimensional feature space, making the subsequent DML task computationally intensive.

To overcome the above limitations, this paper investigates a completely unique framework of Online Multi-modal Distance Metric Learning (OMDML), that learns distance metrics from multi-modal data or multiple types of features via an capable and scalable online learning scheme. Unlike the above concatenation approach, the key ideas of OMDML are two-fold: (i) it learns to optimize a separate distance metric for each individual modality (i.e., each type of feature space), and (ii) it learns to and an optimal combination of diverse distance metrics on multiple modalities. Moreover, OMDML takes advantages of on-line learning techniques for high efficiency and scalability towards large-scale learning tasks. To further minimize the data processing cost, we also propose a Low-rank Online Multi-modal DML (LOMDML) algorithm, which avoids the requirement of doing intensive positive semi-definite (PSD) projections and thus saves a significant amount of computational cost for DML on high-dimensional information. As a summary the major contributions of the paper include: We present a novel framework of Online Multi- modal Distance Metric Learning, which simultaneously learns optimal metrics on each individual modality and also the optimum combination of the metrics from multiple modalities via efficient and scalable on-line learning.

We further propose a low-rank OMDML algorithm which by significantly reducing computational costs for high-dimensional data without PSD projection. We offer theoretical analysis of the OMDML method. We conduct an extensive set of experiments to evaluate the performance of the proposed techniques for CBIR tasks using various types of features. The remainder of this paper is organized as follows. Section 2 reviews related work. Section 3 first gives the problem formulation, and then presents a technique of online multi-modal metric learning, followed by proposing an improved low-rank algorithm. Section 4 provides theoretical analysis for the proposed formula, Section 5 discusses our experimental results, and eventually Section 6 concludes this work. Online Multi-modal Distance Metric Learning (OMDML) are takes in the distance metrics from multi-modal information or multiple sorts of features by means of a productive and versatile online learning plan. To address the confinements of the paper a novel plan of online multi-modal distance metric learning is researched and investigates a bound together two-level online learning plan: (i) first is to learn and improve a different distance metric for every modality. (ii)Second is to learn and locate an ideal mix of various distance metrics on multiple modalities. OMDML takes leverage of online systems for high effectiveness and adaptability towards extensive scale learning assignments. To diminish the computational cost and enhance the exactness of distance metric learning, Low Rank Multi-Modal Distance Metric Learning system is utilized, which it can keep away from the need of concentrated positive semi- unequivocal (PSD) projections and it spares a lot of computational cost for DML on high-dimensional information. A novel system of Low rank multi- modal distance metric learning is presented[2], which at the same time learns ideal metrics on every individual modality with the ideal mix of metrics on every individual modality and the ideal mix of the metrics from multiple sort of modalities by means of effective adaptable for online learning. By and large this strategy is utilized as a part of online learning strategies, rather than online handling strategy the disconnected system is utilized. Online learning is to limit the loss of whole succession of got occurrences.

Fig1: content-based multimedia retrieval

II. LITERATURE SURVEY

Authors "F. Shen, C. Shen, Q. Shi, A. van den Hengel, Z. Tang, and H. T.Shen" [2], described into their paper titled "Hashing on nonlinear manifolds" such as how to learn compact binary embeddings on such intrinsic manifolds is considered. In order to indicate the existing difficulties, an efficient, inductive solution to the out-of-sample data problem and a process by which nonparametric manifold learning may be used as the basis of a hashing method are proposed.

Authors "P. Wu, S. C. H. Hoi, P. Zhao, C. Miao, and Z. Liu" [1], described into their paper titled "Online Multi-Modal Distance Metric Learning with Application to Image Retrieval". This paper is to investigate a novel scheme of online multi-modal distance metric learning (OMDML), which explores a unified two-level online learning scheme: (i) it learns to optimize a distance metric on feature space (ii) then it learns to find the optimal combination of features.

Authors "J.-H. Su, W.-J. Huang, P. S. Yu, and V. S. Tseng" described into their paper titled "Efficient Relevance Feedback for Content-Based Image Retrieval by Mining User Navigation Patterns" such as This paper proposes a magnificent approach, Navigation-Pattern-based Relevance Feedback (NPRF). It is to achieve the high efficiency and effectiveness of CBIR[1] in coping with the large-scale image data set. This new search algorithm NPRF Search can bring out more accurate results than other well-known approaches.

In 2006, Liu et al. proposed two methods for solving this retrieval challenge. The first method used global features like the average gray levels in blocks, the mean and variance of wavelet coefficients in blocks, spatial geometric properties (area, contour, centroid, etc.) of binary ROIs, color histograms, and band correlograms. The second method divided the image into patches and used clusters of high dimensional patterns within these patches as features. Using multiclass support vector machines (SVMs), they were able to achieve a mean average precision of about 68 % when using visual features.

III. Proposed Methodology

CBIR is an image search technique designed to find images that are most similar to given query. It complements text-based retrieval by using quantitative and objective image features as the search criteria. Essentially, CBIR measures the similarity of two pictures based on the similarity of the properties of their visual components, which might the color, texture, shape, and spatial arrangement of regions of interest (ROIs). The nonreliance of CBIR on labels makes it ideal for large repositories where it is not feasible to manually assign keywords and other annotations. The objective features utilized by CBIR mean that it is also possible to show what pictures are similar and to explain why they're similar in an objective, non qualitative manner. The *what* is essentially the set of retrieved images; the why is the difference in specific image features are between the query and the retrieved results. The major challenges for CBIR include the application-specific definition of similarity (based on users criterion), extraction of image features that are relevant to the definition of similarity, and organizing these features into indices for fast retrieval from massive repositories. The choice of features is a critical task when designing a CBIR system because it is closely related to the definition of similarity. Features fall into several categories. General purpose features can be extracted from the all pictures but are not necessarily appropriate for all applications, e.g., color is inappropriate for grayscale ultrasound pictures.

Application-specific features are tuned to a particular problem and describe characteristics unique to a particular problem domain; they are semantic features intended to encode a specific meaning. Global features capture the overall characteristics of a picture but fail to identify important visual characteristics if these characteristics occur in exactly a relatively small part of an picture. Local features describe the characteristics of a small set of pixels (possibly even one pixel), i.e., they represent the details. In recent years, there has been a shift towards using local features largely driven by the idea that almost all images are too complex to be described in a general manner; however, the combination of local and global features remains an area of investigation for practical computer vision applications.

Algorithm 1: Hashing Algorithm

Input: Database images: fIngNn=1, query image q. Output: Hash codes of database images: Y, hash functions: F. Image retrieval results for image query q.

Step 1:Offline Learning

Extract features of database images, obtaining Y(1); Y(2);

- Compute visual graph Laplacian matrix LG;
- Compute topic hypergraph Laplacian matrix LTHG ;
- Learn relaxed hash codes;
- Construct hash functions G ;
- Insert database images into binary hash codes with G;

Step 2:Online Hashing

Extract visual features of query image;

- Project query visual features into the hash codes;
- Calculate the Hamming distances between hash codes of query image and that of database images;
- Rank Hamming distances and return high ranked retrieval results.

IV. Experimentation Results

After successful execution of project, fig 2 is the home page of the project which has several options in it.

Fig2: Home page

We have admin and user to search the images show. If we want to search the image we should login into the browzer as shown in fig3. User will search the images which they required, and admin will upload the images. Admin have all the rights to see what the user is searching as shown in fig4 history of all the images

There are multiple categerious of images are there shown in fig6 from all these categere images are inserted. From all these various types of images, we have the distance metric to all the images in fig5.

Fig3: User Login

Fig4: Search all the images

V.

Fig5: Distance based images

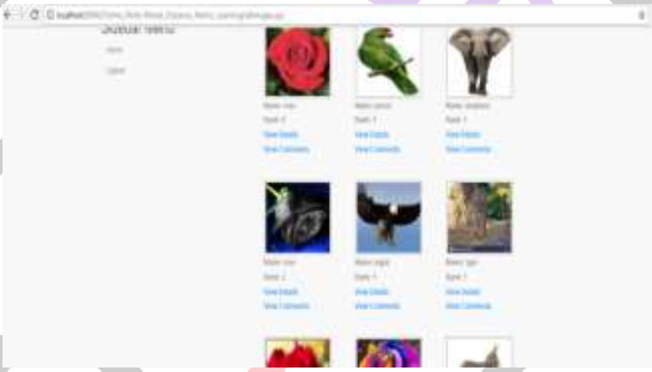

Fig6 :Multi modal images

VI. Conclusion

This paper investigated a novel family of online multi-modal distance metric learning (OMDML) algorithms for CBIR tasks with the exploitation of various types of features. We pinpointed the serious limitations of traditional DML approaches in practice, and presented the online multi-modal DML method which simultaneously learns both the optimal distance metric on each individual feature space and the optimal combination of the metrics on various types of features. We further proposed the low-rank online multi-modal DML algorithm (LOMDML), which not only runs more efficiently and scalably, but also attains the state-of-the-art performance among all the competing algorithms as observed from our extensive set of experiments.

Future Work

It can be extended to medical applications that address both theoretical and real-time challenges of the OMKS framework proposed for the use of large-scale applications28. Noise in the image samples can be removed in pre-processing stage, important features can be selected for ranking visual similarity search, and relevance feedback learning based content based image retrieval can also be extended additionally to enhance medical image applications in content based image retrieval in medical applications.

REFERENCES

[1] J.-H. Su, W.-J. Huang, P. S. Yu, and V. S. Tseng, ―Efficient relevance feedback for content-based image retrieval by mining user navigation patterns.‖ IEEE Trans. Knowl. Data Eng., vol. 23, no. 3, pp. 360–372, 2011.
[2] P. Wu, S. C. H. Hoi, P. Zhao, C. Miao, and Z. Liu, ―Online multi-modal distance metric learning with application to image retrieval,‖ IEEE Trans. Knowl. Data Eng., vol. 28, no. 2, pp. 454–467, 2016.
[3] J. Song, Y. Yang, Z. Huang, H. T. Shen, and J. Luo, ―Effective multiple feature hashing for large-scale near-duplicate video retrieval.‖ IEEE Trans. Multimedia, vol. 15, no. 8, pp. 1997– 2008, 2013. [4] J. Song, Y. Yang, Z. Huang, H. T. Shen, and R.

Hong, ―Multiple feature hashing for real-time large scale near-duplicate video retrieval,‖ in Proc. ACM Int. Conf. Multimedia (MM), 2011, pp. 423– 432.
[5] V. Jagadeesh, R. Piramuthu, A. Bhardwaj, W. Di, and N. Sundaresan, ―Large scale visual recommendations from street fashion images,‖ in Proc. ACM SIGKDD Int. Conf. Knowledge Discovery and Data Mining (SIGKDD), 2014, pp. 1925–1934.
[6] J. Sivic and A. Zisserman, ―Video Google: A text retrieval approach to object matching in videos,‖ in Proc. IEEE Int. Conf. Computer Vision and Pattern Recognition (CVPR), 2003, pp. 1470–1477.
[7] P. Ciaccia, M. Patella, and P. Zezula, ―M-tree: An efficient access method for similarity search in metric spaces,‖ in Proc. Int. Conf. Very Large Data Bases (VLDB), 1997, pp. 426–435.
[8] J. Wang, H. T. Shen, J. Song, and J. Ji, ―Hashing for similarity search: A survey,‖ CoRR, vol. abs/1408.2927, 2014.
[9] L. Gao, J. Song, X. Liu, J. Shao, J. Liu, and J. Shao, ―Learning in high-dimensional multimedia data: the state of the art,‖ Multimedia Syst., pp. 1–11, 2015.
[10] G. H. J. Goldberger, S. Roweis and R. Salakhutdinov, "Neighbourhood components analysis," in *Advances in Neural Information Processing Systems*, 2005.

About authors:

M .VINUTHNA is a mtech scholor of Prasad V Potluri Siddhartha Institute of Technology, Vijayawada.

CH. RATNA JYOTHI is presently working as Assistant professor in CSE department, Prasad V Potluri Siddhartha Institute of Technology, Vijayawada.

A. YUVA KRISHNA is presently working as Assistant Professor in CSE department, Prasad V Potluri Siddhartha Institute of Technology, Vijayawada.