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Image Annotation by Using Dictionary Learning Approach

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Abstract: ***Image annotation has attracted a lot of research interest, and multi-label learning is an effective technique for image annotation. How to effectively exploit the underlying correlation among labels is a crucial task for multi-label learning. Most existing multi-label learning methods exploit the label correlation only in the out-put label space, leaving the connection between the label and the features of images untouched. Although, recently some methods attempt toward exploiting the label correlation in the input feature space by using the label information, they cannot effectively conduct the learning process in both the spaces simultaneously and there still exists much room for improvement. Multi-Label learning approach, named Multi-Label Dictionary Learning (MLDL) with label consistency regularization and partial-identical label embedding MLDL, which conducts MLDL and partial-identical label embedding simultaneously. In the input feature space, it incorporates the dictionary learning technique into multi-label learning and designs the label consistency regularization term to learn the better representation of features. In the output label space, it design the partial-identical label embedding, in which the samples with exactly same label set can cluster together, and the samples with partial-identical label sets can collaboratively represent each other. Experimental results on the three widely used image datasets, including Corel 5K, IAPR TC12, and ESP Game, demonstrate the effectiveness of the proposed approach.***

Keywords: Automatic Image annotation, Training image features, MLDL, Corel5K, IAPR, Testing image features.

1. INTRODUCTION

Digital Images are currently widely used in Fashion, Architecture, F ace Recognition, Finger Print Recognition ,so efficient image searching and retrieval are important. With widely increasing clustering of image data on and off the Web, robust image search and retrieval is fast becoming a difficult requirement. Accurately retrieve images from huge collections of digital photos has become an important research topic. Content-Based Image Retrieval (CBIR) addresses this challenge by finding the matched images based on their visual similarity to a query image.[6] Automatic Image Annotation is a promising research topic and is still an important open problem in multimedia and computer vision fields, which has attracted much researcher's interest. The objective of image annotation is to automatically annotate an image with appropriate keywords, i.e., labels, which reflect visual content in the image. Automatic image annotation is a key step towards semantic keyword based image retrieval, which is considered to be a convenient and easy way for retrieving images on the web. It plays an important role in bridging the semantic gap between low-level features used to represent images and high level semantic labels used to describe image content [1]. With the increasing number of images in social network and on the sharing websites (Facebook, Flicker, and YouTube, etc.), there is a huge demand for automatic image annotation.[2] However due to the semantic gap between the low-level visual features used to represent images and the high-level semantic tags used to describe image content, limited performance is achieved by CBIR techniques. To address the limitation of CBIR, many algorithms have been developed for Tag Based Image Retrieval (TBIR) that represents images by manually assigned keywords/tags. It allows a user to resent his/her details needs by textual represented and find the relevant images based on the match between the textual query and the assigned image tags. Recent studieshave shown that TBIR is usually more effective than CBIR in identifying the relevant images[3] Since it is time-consuming to manually label images, various methods have been developed for automatic image annotation etc. One of the most extensively researched directions is the generative model based image annotation, such as. Generative model based image annotation methods are usually dedicated to maximizing generative likelihood of image features and labels. However, generative models may not be rich enough to accurately capture the intricate dependencies between image features and labels[1][2][3]. Based on the assumption that visually similar images are more likely to share common labels, many non-parametric nearest neighbor models have been developed. They compute the similarities between training samples and the given query sample, and propagate labels of the few training samples that are most similar to that query sample to the query sample. The similarity of images is determined by the average of several distances computed from different visual features. These nearest neighbor model based methods are simple, yet they may fail when the number of training examples is limited.[4].

The aim of this project is to annotate image for effective searching The objective of Image Annotation is to automatically annotate an image with appropriate keywords, i.e., labels, which reflect visual content in the image. Automatic Image Annotation is a key step towards semantic keyword based image retrieval, which is considered to be a convenient and easy way for retrieving images on the web[4][5].

OBJECTIVES

- To illustrate the benefits of using semantic technologies in image annotations.
- To provide guidelines for applying semantic technologies in this area.
- To collect currently used vocabularies for Semantic Web-based image annotation.
- To provide use cases with examples of Semantic Web-based image annotation

2. LITERATURE SURVEY

Literature Survey is the most important step in software development process. Before start developing the software it is necessary to keep in mind the time factor, economy and industrial strength. These things are full-fill, then next step is to determine which os and language can be used for building the tool. When programmers start building the tool it need external support. This support can be obtained from senior programmers, from book or from websites. We have to take consideration before building the system the above into account for developing the proposed system.

Y. Verma and C. V. Jawahar, Conclude that "Image annotation using metric learning in semantic neighborhoods,[2012]". Automatic image annotation aims at predicting a set of textual labels for an image that describe its semantics. These are usually taken from an annotation vocabulary of few hundred labels. Because of the large vocabulary, there is a high variance in the number of images corresponding to different labels (\class-imbalance").Additionally ,due to the limitations of manual annotation, a significant number of available images are not annotated with all the relevant labels (\weak-labelling"). These two issues badly a ect the performance of most of the existing image annotation models. In this work, we propose 2PKNN, a two-step variant of the classical K-nearest neighbour algorithm, that addresses these two issues in the image annotation task The rest step of 2PKNN uses \image-to-label" similarities, while the second step uses \image-to-image" similarities; thus combining the benefits of both. Since the performance of nearest neighbour based methods greatly depends onhow features are compared, we also propose a metric learning frame-work over 2PKNN that learns weights for multiple features as well as distances together. This is done in a large margin set-up by generalizing a well-known (single-label) classification metric learning algorithm for multi-label prediction. For scalability, we implement it by alternating between stochastic sub-gradient descent and projection steps. Extensive experiments demonstrate that, though conceptually simple, 2PKNN alone performs comparable to the current state-of-the-art on three challenging image annotation datasets, and shows significant improvements after metric learning[4][5][6].

T. S. Huang, Conclude that "Multi-label image categorization with sparse factor representation,[2014]".

J. R. Wen, Conclude that "Semantic sparse recoding of visual content for image applications,[2015]".

Most existing multi-label learning methods exploit the label correlation only in the output label space, leaving the connection between the label and the features of images untouched. Although, recently some methods attempt toward exploiting the label correlation in the input feature space by using the label information, they cannot effectively conduct the learning process in both the spaces simultaneously, and there still exists much room for improvement. In this paper, we propose a novel multi-label learning approach, named multi-label dictionary learning (MLDL) with label consistency regularization and partial-identical label embedding MLDL, which conducts MLDL and partial-identical label embedding simultaneously. In the input feature space, we incorporate the dictionary learning technique into multi-label learning and design the label consistency regularization term to learn the better representation of features. In the output label space, we design the partial-identical label embedding, in which the samples with exactly same label set can cluster together, and the samples with partial-identical label sets can collaboratively represent each other. Experimental results on the three widely used image datasets, including Corel 5K, IAPR TC12, and ESP Game, demonstrate the effectiveness of the proposed approach.

Due to more number of images being generated in digital form. It is important to deal with a problem of extracting content base images and then retrieve these images effectively. Humans tend to interpret images using concepts they are able to find keywords, abstract objects or events presented in the image. However, for a computer the image features matrix of pixels, which can be summarized by low-level color, shapes features. There is miss correlation between the high-level concepts that a user requires and the low-level features that image retrieval offer the semantic gap[7][8].

Xiao-Yuan Jing, Fei Wu, Zhiqiang Li, Ruimin Hu and David Zhang,Propose that it can conduct multi-label dictionary learning in input feature space and partial-identical label embedding in output label space, simultaneously. In the input feature space, MLDL incorporates the label consistency regularization term into multi-label dictionary learning to learn discriminative representation of features. In the output label space, MLDL learns the partial-identical label embedding, where samples with the exactly same label set can cluster together and samples with partial-identical label sets can collaboratively represent each other, to fully utilize the relationship between labels and visual feature[6]. The earlier image retrieval systems were based on text. Images were represented by using text. The label for the image was created by human. Manually entering label for images in a huge database can be inefficient, expensive and may not capture every label that represented the image search. Therefore, content based image retrieval, based on the image content came into existence[9].

PROBLEM STATEMENT

Now a day's images are widely used in architecture, fashion, bio-metric scan etc. Hence, useful image searching and retrieval are important. With rapidly increasing collections of image data on and off the Web, robust image search and retrieval's fast becoming a critical requirement. The objective of image annotation is to automatically annotate an image with appropriate keywords, i.e., labels, which reflect visual content in the image. Automatic image annotation is a key step towards semantic label based image searching, which is treated to be a convenient and easy way for retrieving images on the web[10].

3. SYSTEM ARCHITECTURE

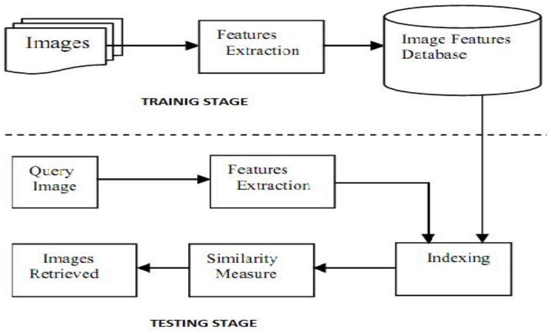

Fig. 1. Architecture

The system architecture is divided into two stages :
Training stage and Testing stage.
1]Training Stage: In the training stage the first we have to train our image by adding labels manually to it.After Adding manually label to that particular image the feature extraction is done on the basis of Color extraction by RGB-HSV model and the texture and edges of the images extracted by canny-edge detector algorithm. After extracting the features of the images all the features stored in the database by properly indexing to them[10].
2]Testing Stage: In the testing stage the user has to give input image and then the extraction is done on the basis of color extraction and shape and texture features. After extracting the features all extracted features are converted in the binary coded matrix and the features are also compared with the existing database features. And it retrieve the most highly matched features of both extracted features and existing features and add automatically labels to the particular given input image[11].

4. RESULTS

Following screen shots shows the implementation results of the proposed method.

Fig. 2. Main Menu

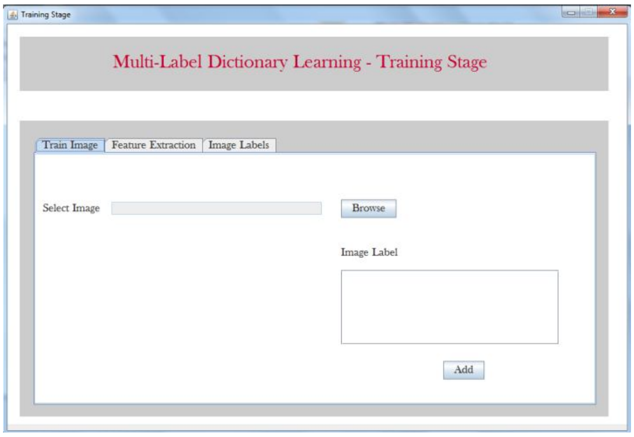

Fig. 3. Training Stage

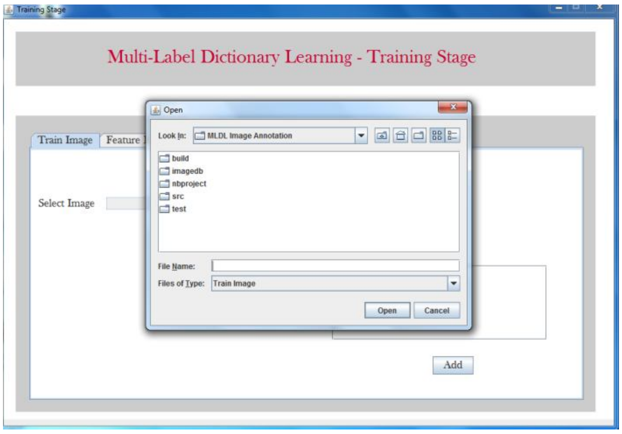

Fig. 4. Browse File

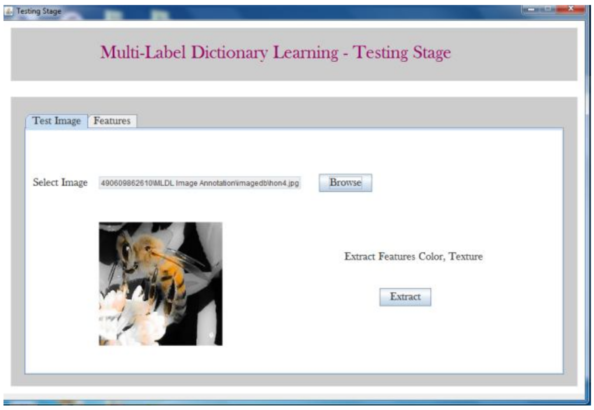

Fig.5. Chosen Files

5. CONCLUSION

Image Annotation Approach named MLDL. It can conduct Multi-Label Dictionary Learning in input feature space and partial-identical label embedding in output label space, simultaneously. In the input feature space, MLDL incorporates the label consistency regularization term into multi-label dictionary learning to learn discriminative representation of features. In the output label space, MLDL learns the partial-identical label embedding, where samples with the exactly same label set can cluster together and samples with partial-identical label sets can collaboratively represent each other, to fully utilize the relationship between labels and visual features. Apply MLDL for image annotation task on three widely used datasets. The experimental results demonstrate that MLDL can outperform several state-of-the-art related methods generally and obtain desirable annotation effects further perform experiments to evaluate the designed partial-identical label embedding and label consistency regularization term. The corresponding experimental results validate their effectiveness. Also evaluate the semantic retrieval performance of this approach, and the retrieval results indicate MLDL is effective for semantic retrieval .

REFERENCES

[1] Deepak A Vidhate and Parag Kulkarni, "New Approach for Advanced Cooperative Learning Algorithms using RL Methods (ACLA)" Proceedings of the Third International Symposium on Computer Vision and the Internet, ACM, pp 12-20, 2016

[2] J. Jeon, V. Lavrenko, R. Manmatha, "Automatic image annotation and retrieval using cross-media relevance models," in Proc. 26th Annu. Int. ACM SIGIR Conf. Res. Develop. Inf. Retr., 2003, pp. 119–126.

[3] Deepak A Vidhate and Parag Kulkarni, "Innovative Approach Towards Cooperation Models for Multi-agent Reinforcement Learning (CMMARL)", Springer Nature series of Communications in Computer and Information Science, Vol. 628,pp. 468-478,2016

[4] R. Datta, D. Joshi, J. Li, and J. Z. Wang, "Image retrieval: Ideas, influences, and trends of the new age," ACM Compute. Surv., vol. 40 no. 2, 2008

[5] C. Wang, S. Yan, L. Zhang, and H. J. Zhang, "Multi-label sparse coding for automatic image annotation," in Proc. IEEE Conf. Comput. Vis.Pattern Recognition., Jun. 2009, pp. 1643–1650.

[6] Y. Verma and C. V. Jawahar, "Image annotation using metric learning in semantic neighbourhoods," in Proc. 12th Eur. Conf. Comput. Vis., 2012,pp 836,849.

[7] Deepak A Vidhate and Parag Kulkarni, "Single Agent Learning Algorithms for Decision making in Diagnostic Applications", SSRG International Journal of Computer Science and Engineering (SSRG-IJCSE), Vol.3, No.5,pp.46-52,2016

[8] D. Boneh and M. K. Franklin, "Identity-Based Encryption from the Weil Pairing," in Proceedings of Advances in Cryptology – CRYPTO '01, ser. LNCS, vol. 2139. Springer, 2001, pp. 213–229.

[9] Deepak A Vidhate and Parag Kulkarni, "Implementation of Multiagent Learning Algorithms for Improved Decision Making", International Journal of Computer Trends and Technology (IJCTT) Vol 35, No 2,pp 60-66, 2016

[10] Deepak A Vidhate and Parag Kulkarni (2014): ""To improve association rule mining using new technique: Multilevel relationship algorithm towards cooperative learning", International Conference on Circuits, Systems, Communication and Information Technology Applications (CSCITA), pp 241—246, 2014 IEEE

[11] Deepak A Vidhate and Parag Kulkarni, "Performance enhancement of cooperative learning algorithms by improved decision making for context based application", International Conference on Automatic Control and Dynamic Optimization Techniques (ICACDOT)IEEE Xplorer, pp 246-252, 2016