Research Article | Impact Factor: 0.621 | ISSN: 2319-507X
Nischal Puri, IJPRET, 2014; Volume 2 (9): 52-58 | IJPRET

INTERNATIONAL JOURNAL OF PURE AND APPLIED RESEARCH IN ENGINEERING AND TECHNOLOGY

A PATH FOR HORIZING YOUR INNOVATIVE WORK

A SURVEY - IMAGE ANNOTATION TECHNIQUES

PROF. NISCHAL PURI, MS. DEEPALI D. GIRI

Department of Information Technology, Priyadarshini Institute of Engineering & Technology

Accepted Date: 27/02/2014 ; Published Date: 01/05/2014

Abstract: This paper provides an introduction to Automatic image annotation and also will converse the literature survey on various approaches for automatic annotation on digital images. Nowadays digital photography is a common technology for capturing and archiving images due to the falling price of storage devices and digital cameras. In this paper we focus on different techniques of automating the process of annotating images as an intermediate step in retrieval process. There are some researches on image annotation which provides very good knowledge theoretically or technically that lead to produce such promising surveys. Automatic image annotation is the process of assigning keywords to digital images depending on the content information. Many techniques have been proposed for image annotation in the last decade that gives reasonable performance on standard datasets. Summary and analysis of some of the approaches have been used as references to create a framework in designing an automatic image annotation.

Keywords: Privacy, Oauth, Collaboration, Recommendation Social Networks

Corresponding Author: PROF. NISCHAL PURI

Access Online On:

www.ijpret.com

How to Cite This Article:

Nischal Puri, IJPRET, 2014; Volume 2 (9): 52-58

PAPER-QR CODE

INTRODUCTION

the contain information. Automatic image annotation (AIA) plays an important role and attracts much research attention in image understanding and retrieval. In one sense, it is a mapping from the visual contains information to the semantic context information. Assignment of the words to images depends on several criteria.

1) Segmental Approaches: This group of studies considers the image as consisting of semantically meaningful parts and tries to find a probabilistic relation between the parts of the image and the keywords. For this purpose, images are segmented or parts are taken from the image and features are extracted from these parts.

2) Holistic Approaches: This group considers the image as a whole. Features are extracted from the whole image. And a relation is explored directly between the image and the annotation words.

sea, sun, sky, waves

cat, forest, grass, tiger

Image Annotation

Image annotation has been an active research topic in recent years because of its potentially high impact on Web Image search. To affectively access and retrieve images, a widely adopted solution is to tag images with meaningful keywords semantically called image annotation. There are three types of image annotation

A. Manual annotation

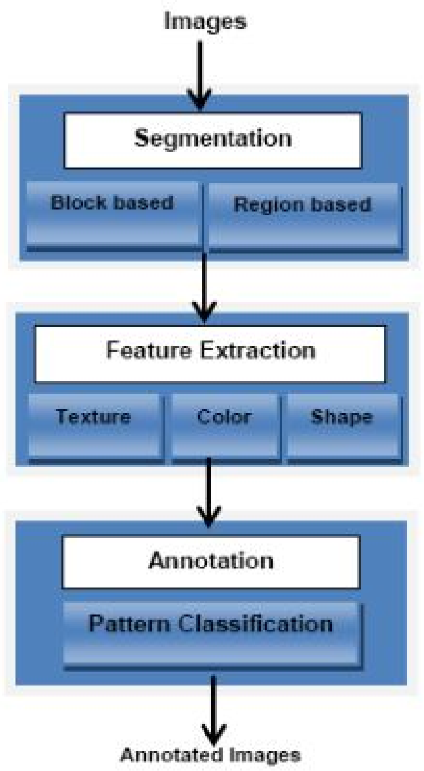
B. Semi-automatic image annotation

C. Automatic

Annotation Techniques	Manual	Automatic	Semi Automatic
Advantages	The most accurate annotation	The most efficient, the least time	Quality of the annotation improves in an interactive manner after human correction
Disadvantages	Time consuming (expensive), difficult, subjective, inconsistency	The less accurate annotation	Less time than automatic annotation, greater time than manual annotation

Comparison of Annotation Techniques

Manual annotation needs users to enter some descriptive keywords when execute image browsing. While automatic annotation detects and labels semantic content of images with a set of keywords automatically. In the case of semi-automatic annotation, it needs user's interaction to provide an initial query and feedback for image annotation while browsing. Manual image annotation is considered expensive and time consuming. While semi annotation is very efficient compared to manual annotation and more accurate than automatic annotation. Automatic image annotation is the best in term of efficiency but less accuracy. [1]



Typical Image annotation framework

Various Techniques of Image Annotations

1. Semi-Supervised Learning Model

This technique propose a novel approach to annotate images based on a semi-supervised learning model, random walk with restart algorithm, where the information of both the candidate annotations and the corpus can be well integrated to achieve precise interrelation among semantic annotations. Automatic image annotation, which contains two components. More specifically, the candidate annotations are first chosen through a progressive relevance model approximating the joint probability of multiple words. Then, the significance of candidate annotations is re-ranked by a semi-supervised learning model, i.e., random walk with restart learning algorithm. Lastly obtained annotations can better reflect image visual content and consist with human perception. [3]

2. Cross Media Relevance Models

In this technique every image may be described using a small vocabulary of blobs. Using a training set of annotated images, we study the joint distribution of blobs and words which we call a cross-media relevance model (CMRM) for images. There are two ways this model can be used. [4]

A) Probabilistic annotation-based cross media relevance model (PACMRM)

This corresponds to document based expansion, the blobs corresponding to each test image are used to generate words and associated probabilities from the joint distribution of blobs and words. Each test image can, therefore, be annotated with a vector of probabilities for all the words in the vocabulary. [4]

B) Fixed annotation based cross-media relevance model (FACMRM)

PACMRM model is useful for ranked retrieval; it is less useful for people to look at. Fixed length annotations can be generated by using the top N (N = 3, 4 or 5) words (without their probabilities) to annotate the images. It is easy for people to use when the number of annotations is small. [4]

3. Continuous-space Relevance Model (CRM)

On the surface, CRM appears to be very similar to one of the intermediate models considered by Blei and Jordan [5]. Specifically, their *GM-mixture* model employs a nearly identical dependence structure among the random variables involved. However, the topological structure of CRM is somewhat different from the one employed by [5]. GM-mixture assumes a low-dimensional topology, leading to a fully-parametric model where 200 or so “latent aspects” are estimated using the EM algorithm. To contrast that, CRM makes no assumptions about the topological structure, and leads to a doubly non-parametric approach, where expectations are computed over every individual point in the training set. In that regard, CRM appears very similar to the cross-media relevance model. [6]

RELATED WORK UNDER AIA

Recently, there has been some work on automatically annotating images by looking at the probability of associating words with image regions. Mori *et al.* [7] proposed a *Co-occurrence Model* in which they focused at the co-occurrence of words with image regions created using a regular grid. Duygulu *et al* [8] proposed to describe images using a vocabulary of blobs. First, regions are created using a segmentation algorithm like normalized cuts. For each region, features are computed and then blobs are generated by clustering the image features for these regions across images. Each image is generated by using a certain number of these blobs. Their *Translation Model* applies one of the classical statistical machine translation models to translate from the set of keywords of an image to the set of blobs forming the image. Jeon et al [4] instead assumed that this could be viewed as analogous to the cross-lingual retrieval problem and used a cross-media relevance model (CMRM) to perform both image annotation and ranked retrieval. They showed that the performance of the model on the same dataset was considerably better than the models proposed by Duygulu *et al* [8] and Mori *et al.* [7]

CRM appears very similar to the cross-media relevance model (CMRM) [4], which is also doubly non-parametric. There are two significant differences between CRM and CMRM. First, CMRM is a discrete model and cannot take advantage of continuous features. In order to use CMRM for image annotation we have to quantize continuous feature vectors into a discrete vocabulary (similarly to the co-occurrence and translation [8] models). CRM, on the other hand, directly models continuous features. The second difference is that CMRM relies on *clustering* of the feature vectors into *blobs*. Annotation quality of the CMRM is very sensitive to clustering errors, and depends on being able to a-priori select the right cluster granularity: too many clusters will result in extreme sparseness of the space, while too few will lead us to confuse different objects in the images. CRM does not rely on clustering and consequently does not suffer from the granularity issues. [6]

CURRENT RESEARCH

Images are annotated to simply access to them by using metadata that being added to images in order to allow more effective searches. If the images are described by textual information, then text search technique can be used to perform images searches. However, there is a need to improve generation of automated metadata for images called automatic image annotation. By using this method, allow image searches using CBIR more effective. Image annotation surveys have been reviewed by many researchers according to the demanding the needs for annotating images.

Rami ALBATAL, Philippe MULHEM, Yves CHIARAMELLA in 2011 propose model "A NEW ROI GROUPING SCHEMA FOR AUTOMATIC IMAGE ANNOTATION" [9] where the regions of Interest (ROI) are successfully used in automatic image annotation through Bag of Visual Words (BoVW) models. Based on the phrasing model, this paper proposes a grouping scheme that takes into account topological relationships between the ROI. It shows that the application of such framework in an automatic annotation method significantly overcomes the results of a classic BoVW annotation method. [1]

FUTURE WORKS

The combination of different approaches could bring a improved performance to an AIA system. However, some further extensions of current system could be considered to pick up the annotation performance. In the short-term vision, our goal is to extend the current framework on other kind of image representations, for example, regular grid portioning and graph-based model. Future work will also involve an automatic image features selection process for each category of image.

For a long-term perspective, automatic video annotation is an interesting issue that currently requires for a lot more research efforts. The annual TRECVID conference draws many attentions of research community in content-based retrieval of digital videos. One of the major objectives of this forum is to benchmark state-of-the-art algorithms for multimodal analysis of digital media targeting semantic retrieval. [10]

CONCLUSION

Image annotation is an emerging field in the 21st century. A survey of the field of Automatic image annotation is given in this paper. We have presented three different models a semi-supervised learning model, Cross Media Relevance Models and Continuous-space Relevance Model (CRM) to complete the task of automatic image annotation. We also describe various image annotation definitions & techniques. By obtaining the large amounts of labeled training and test data is difficult but we believe this is needed for improvements in both performance and evaluation of the algorithms. Better feature extraction or the use of continuous features will probably improve the results. Other areas of possible research include the use of actual captions (instead of keywords). We believe that this is a fruitful area of research for applying formal models of information retrieval. Various research of automatic image annotation has been discussed. Moreover, we mentioned different tools that are utilized in automatic image annotation Finally we had shown the current research trends in this new era of automatic image annotation. Image annotation brings a lot of benefits to businesses; society, governments as well as individual. However image retrieval is the big problem if it is not address correctly. Our contribution addresses the challenges in automatic image annotation.

REFERENCES

1. Miss. Hemlata Sahu & Proff. Mr. Hitesh Gupta "An Approach to Review on Automatic Image Annotation: A Survey", International Conference on Computing and Control Engineering (ICCCE 2012), 12 & 13 April, 2012

2. T. Sumathi, C.Lakshmi Devasena and M.Hemalatha "An Overview of Automated Image Annotation Approaches" by International Journal of Research and Reviews in Information Sciences Vol. 1, No. 1, March 2011

3. Songhao Zhu and Yuncai Liu "Semi-Supervised Learning Model Based Efficient Image Annotation", IEEE SIGNAL PROCESSING LETTERS, VOL. 16, NO. 11, NOVEMBER 2009

4. J. Jeon, V. Lavrenko, and R. Manmatha "Automatic image annotation and retrieval using cross-media relevance models," in *Proc. ACM SIGIR*, 2003, pp. 119–126.

5. D. Blei, and M. I. Jordan "Modeling annotated data", in *Proceedings of the 26th Intl.ACM SIGIR Conf.*, pages 127–134, 2003

6. V. Lavrenko, R. Manmatha, J. Jeon "A Model for Learning the Semantics of Pictures" by,

7. Y. Mori, H. Takahashi, and R. Oka "Image-to-word transformation based on dividing and vector quantizing images with words" in *MISRM'99 First Intl. Workshop on Multimedia Intelligent Storage and Retrieval Management*, 1999.

8. P. Duygulu, K. Barnard, N. de Freitas, and D. Forsyth "Object recognition as machine translation: Learning a lexicon for a fixed image vocabulary". In Seventh European Conf. on Computer Vision, pages 97-112, 2002.

9. Rami albatal, Philippe mulhem, Yues chiaramella "A new roi grouping schema for automatic image annotation", 978-1-61284-350-6/11/$26.00 ©2011 IEEE

10. Trong-Tˆ on Pham "Master Thesis on Automatic Image Annotation: Towards a Fusion of Region-based and Saliency-based Models" by, UNIVERSITE PIERRE ET MARIE CURIE MASTER IAD, September 2006.