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An Automatic Image Annotation Technique Based on Coverage Ratio of Tags

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Abstract— **In this paper we propose an automatic image annotation technique. The proposed technique is based on coverage ratio of tags by employing both image content and metadata. The images in a reference image set are employed to automatically annotate a given image according to the coverage ratio of the tags in the reference image. Tags and content descriptors as well as coverage ratio of the tags are generated for the entire images in the reference image set. The color and texture content descriptors are employed to retrieve similar images for an un-annotated image from reference image data set and the tags in the metadata of the retrieved images are used to annotate the un-annotated image. Simulation results indicate that the proposed technique outperforms another automatic annotation technique that uses similar content descriptors both in average precision and average recall.**

Keywords- ***coverage ratio; image content; image metadata; discrete wavelet transform; color histogram; automatic annotation***

I. INTRODUCTION

The number of the produced digital images grows rapidly and as a consequence the need for effective management and retrieval of digital images in large databases increases as well. There are two main approaches for image retrieval: text based and content based. Text based image retrieval method are introduced in the mid-70s. These methods employed information retrieval (IR) models such as Boolean model, vector space model and probabilistic model [1] and IR techniques such as term weighting, query modification [1] and suffix stripping [2]. These methods retrieve similar images based on a textual description given for the image. Text based retrieval methods suffer from two main problems. First, they need a person to annotate the images. It is a very time consuming process especially for large image databases. Second, the annotation depends on the annotator and will be different if performed by various people. Content based image retrieval (CBIR) is proposed in the 1980s to solve the problems associated with text based image retrieval. CBIR employs low level features of the image such as color, texture and shape to provide a description for a given image. Color histogram [3], Gabor texture descriptor [4], edge histogram [5], shape representation [6] and many other feature vectors that are listed in the MPEG-7 international standard [7] are among the features that can be used in CBIR. Various methods are introduced to employ descriptors in the image retrieval process e.g. Semantic modeling [8], image ALIP and Boolean matching [9] and combining low-level features [10].

Even though CBIR provides satisfactory results in a number of applications, it suffers from the problems associated with semantic gap between high level concepts in the image and the low level feature of the image. As a result image retrieval methods based on combining image content and metadata have attracted a great deal of attentions in the recent years. Web based image retrieval by using clustering algorithms [11], image retrieval based on image content and tags [12] and bridging the semantic gap between image content and image tags [13] are among the papers which employ image content and metadata for image analysis and retrieval. J. M. Barrios et al. [12] employed metadata available in the webpage such as image name, block label and textual information on the webpage of the image besides the image content information. They compute the distance between text and content descriptors of the image and combine the results by using fixed weighting coefficients to produce the final distance metric between two images. H. Ma et al. [13] proposed six descriptors for image textual information and five content descriptors. The user defines the weights for combining these 11 descriptors to result the final similarity metric.

Since image annotation is a time consuming process in the image retrieval methods which are based on image content and metadata, there are proposed techniques to generate tags by analyzing image content. L. Jiang et al. [14] proposed a bisectional graph to indicate the relation between textual and content features of an image. This graph is generated based on text and content features which derived from a learning image set. A graph is based on the distance between content descriptors and another graph is based on the amount that each tag is related to the given image. In the next stage these graphs are merged to produce a bisectional graph including the information about content descriptors and textual descriptors of the image. A transition between two nodes in this graph indicates the similarity between two images or an image and a tag. Image analysis is performed based on the similarity among an image and various tags.

A learning model to produce tags based on semantic concepts of images is proposed by Lavrenko et al. [15]. Feng et al. [16] employed Bernoulli relevance model for image and video annotation. They generate a statistical model by using the images in the learning image dataset and employ this model for automatic annotation of new images. Ulges et al. [17] proposed an image annotation method based on learning visual content. Using their approach the annotation for a given image can be modified based on the categorizations provided by the user for the images in the learning image dataset. In this method the similarity of the image with different image groups is evaluated and the image group with highest similarity is selected. The tags of the image are modified according to the images in the most similar group. In this way more precise annotation can be achieved for an image.

Shin et al. [18] have used emotional concepts for image annotation. They infer emotional concepts from the visual content of images. The user selects one relevant and one irrelevant image for each emotional concept. An un-annotated image is compared with the images in the training dataset and its similarity with relevant and irrelevant images is evaluated. The emotional concept of the image is defined according to its evaluated similarities with relevant and irrelevant images.

Wang et al. [19] proposed an ALIP (Automatic Linguistic Indexing of Pictures) system. The ALIP system learns the expertise of a human annotator on the basis of a small collection of annotated representative images. The learned knowledge about the domain-specific concepts is stored as a dictionary of statistical models in a computer-based knowledge base. When an un-annotated image is presented to ALIP, the system computes the statistical likelihood of the image resembling each of the learned statistical models and the best concept is selected to annotate the image. The first process of the ALIP system is the model-based learning process. Before an ALIP system can be used to annotate any images, it must be trained about the domain. For each concept, it is needed to prepare a set of training images. Ideally, these training images should be representative to the concept. For example, if we would like to train the concept “Horse”, we need to use images of different horses rather than different images of the same horse. For each training image, localized features using wavelet transforms are extracted. An image is first partitioned into small pixel blocks. The block size can vary depending on the resolution of images in the collection and the subject of the collection. The block size is chosen to be 4×4 in the reported experiments as a compromise between the texture detail and the computation time. The system extracts a feature vector of six dimensions from each block. The features are extracted using the LUV color space, where L encodes luminance, and U and V encode color information (chrominance). A training database of concepts, each with a small collection of images representing the concept is prepared manually. The system is capable of handling different number of training images per concept. The more diverse a concept is, the more training images can be required to obtain a reasonable training of the system. In the annotation process, first a collection of feature vectors at multiple resolutions are extracted from the image. The technique for extracting the features is the same as the technique used in the training process. The features of an image are considered as an instance of a stochastic process defined on a multi-resolution grid. The similarity between the image and a concept of images in the database is assessed by the log likelihood of this instance under the model trained from images in the concept.

In this paper we propose a new automatic annotation technique which is based on coverage ratio of tags and employs both content and metadata of previously annotated images for annotating new images. We have compared the proposed technique with the ALIP technique proposed in [19] which uses similar descriptors for image content. Simulation results indicate that our technique outperforms ALIP technique by 0.1 and 0.26 in average precision and average recall, respectively.

The rest of paper is organized as follows. In section II the proposed technique is explained. Simulations results are given in section III followed by concluding remarks on section IV.

II. THE PROPOSED APPROACH

A. Basic Idea

In this paper we propose an automatic annotation technique based on coverage ratio of the tags in the previously annotated images. We use a reference image dataset and provide tags and content descriptors for the images in it. Moreover, there is assigned a coverage ratio to each tag which is selected for the image. The content descriptors are automatically generated based on image features such as color and texture. But the tags and their coverage ratios are subjectively assigned to the image by a user.

In the annotation step, content based image retrieval (CBIR) is employed to retrieve similar images to a given un-annotated image from reference image dataset using the image content descriptors. The annotation of the image is performed according to the tags of the retrieved images and their associated coverage ratio. We believe that the proposed coverage ratio based automatic annotation technique is a powerful tool for automatic annotation of the images and simulation results confirms our idea. In the next subsection we explain our proposed technique in more detail.

B. The Proposed Technique

In the first stage of our automatic annotation method a person annotates a reference image set using a limited number of tags. In this stage the user assigns a coverage ratio to each selected tag as well. The coverage ratio indicates the approximate percentage of the image area which is related to the selected tag, according to the annotator. We have implemented a user interface (UI) to get this annotation information for the images in the reference set from the user. Fig. 1 indicates the implemented UI.

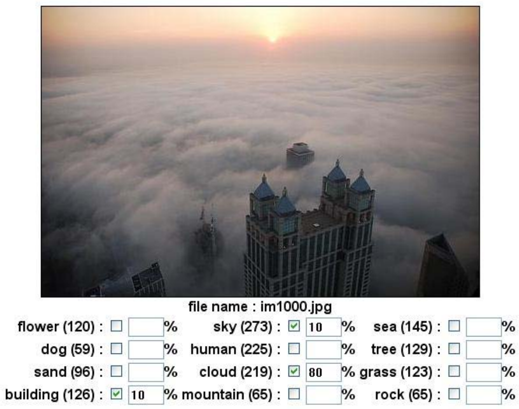


Figure 1. The UI for annotation of the images in the reference set

The UI shows the selected image and the predefined tags in the below of the image. Each tag in the implemented UI is associated with the number of the images which have already annotated with the tag. For example, Fig. 1 indicates that there have been annotated 273 images with the tag “sky” already. User selects appropriate tags for the given image according to the perceived visual content of the image. Then, the user will assign a coverage ratio number to each selected tag. Coverage ratio number indicates approximate coverage of image by the selected tag. In Fig. 1 there are selected, three tags “sky”, “cloud” and “building” for the given image. The user have assigned coverage ratios of 10% , 80% and 10% to the “sky”, “cloud” and “building” tags, respectively. Even though, the assigned coverage ratio number is not precise, it indicates the approximate coverage of the given image by the selected tag according to the user. The higher the value for the coverage ratio number, the higher will be the importance of the selected tag for the image.

Since the proposed annotation method employs both metadata and image content, it is required that the low level image descriptors are produced for the image reference set besides the metadata tags. Color and texture features are used to produce content based descriptors in our proposed method. The color histograms in the HSV color space are used as the color descriptors. The HSV color space has the advantage that it is correlated with the human perception from colors more than other color spaces [20], [21].

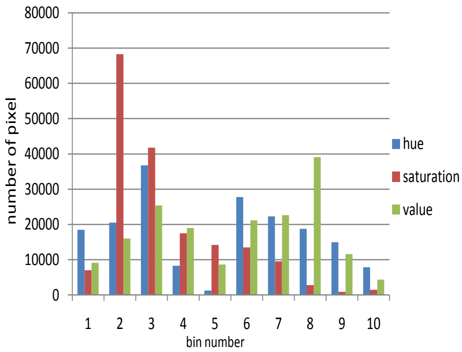
We generated three color histograms for the hue, saturation and value (lightness) components of the HSV representation of the images in the reference set. Each histogram consists of 10 bins and hence there will be 30 bins for the color description of an image. The histogram normalization is performed for each image by dividing each bin value by the total number of pixels in the image. Histogram normalization is done in order to make the histograms independent of the image resolution. Fig. 2 indicates a 500×354 image and its un-normalized and normalized HSV color histograms.

The discrete wavelet transform (DWT) of the luminance component of image is used as the texture descriptor in our experiment. Three level WT is applied to the images in the reference set to produce ten DWT sub-bands. Fig. 3 indicates an image and its 3-level DWT.

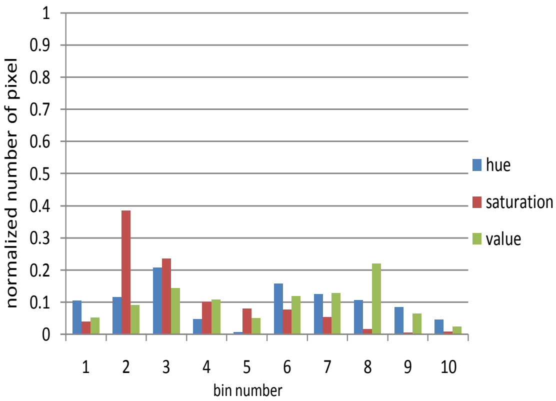
The average and variance of the coefficients in each sub-band are employed to produce texture feature vectors. We divided each element of feature vector by 255 to scale down the resulted 20 elements of texture feature vector. The numbering of the elements of the feature vectors is according to their position in the DWT of the image and is shown in Fig. 4 along with the initial texture feature vector and down scaled feature vector for the image given in Fig. 3. Color and texture feature vectors are generated for each image in the reference image set. In the automatic image annotation process the aforementioned color and texture feature vectors are generated for the query image (Q). The color and texture feature vectors of the image Q are compared with the corresponding feature vectors of each image (I) in the reference set by using the Euclidean distance.

$$d(I,Q) = \sqrt{\sum_{j=1}^{n} (h_j^Q - h_j^I)} \qquad (1)$$

(a)



(b)



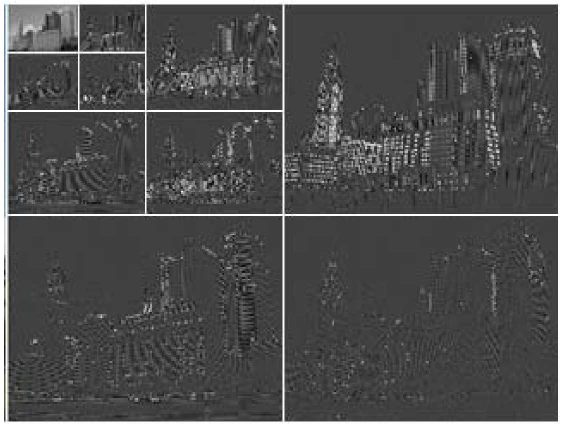
(c)

Figure 2. An image (a) and its un-normalized (b) and normalized (c) HSV color histograms

There will be six Euclidean distances resulting from hue, saturation, value, average and variance feature vectors. The weighted sum of these distances are used to produced the total distance between query image Q and image I in the reference image set as:

$$D_{I,Q} = h \times H + s \times S + l \times L + a \times A + v \times V \quad (2)$$

(a)

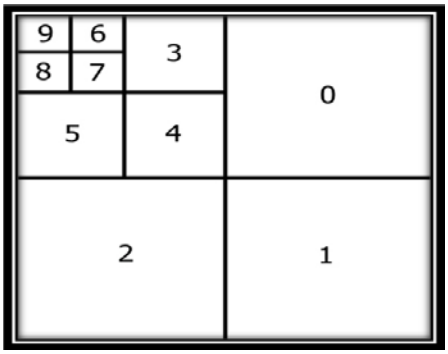


(b)

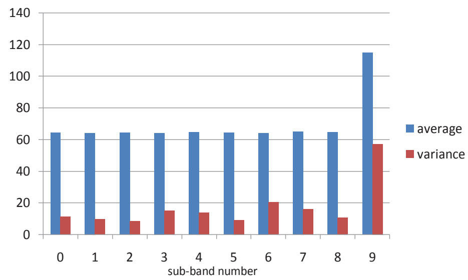
Figure 3. An image (a) and its three level DWT (b)

where h, s, l, a and v are the selected weights for hue, saturation, value, average and variance distances, respectively. $D_{I,Q}$ indicates the total distance between Q and I images according to their color and texture feature vectors. In the retrieval step the images in the reference image set with lowest $D_{I,Q}$ are retrieved as similar images to image Q. The annotation is performed based on the tags of the retrieved images for image Q. the implemented UI for retrieval and annotation step is shown in Fig. 5. As shown in Fig. 5 the user can select the predefined color and texture feature vectors and assign the preferred weight to each feature vector. In Fig. 5 the user has selected all feature vectors and assigned the weights of 10, 5, 5, 45 and 35 for hue, saturation, value, average and variance, respectively. The retrieved images for the given query image in Fig. 5 (No. 232) are shown in Fig. 6.

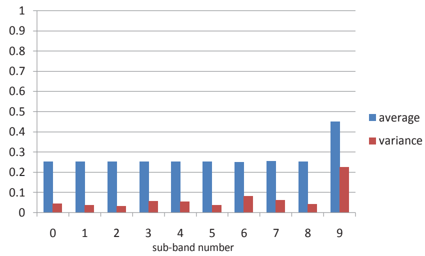
The proposed UI provides extra facilities for the user to improve the retrieval step of annotation process. For example the user can select the number of the first images in the ranked retrieved images (N) that will be used in annotation process. In Fig. 5 the value of 20 is selected for parameter N. The tags of the first N images in the ranked retrieved images which have a coverage ratio number greater than K percent are used in the annotation of image Q. In Fig. 5 the value of 20 is selected for K.



(a)



(b)



(C)

Figure 4. The numbering of the elements of the feature vectors according to their position in the DWT of the image (a) and the initial texture feature vector (b) and down scaled feature vector (c) for the image in Fig. 3

More over the user can select an additional parameter M which indicates that only those tags will be considered in the annotation of image Q that appear in more than M image of the first N retrieved image with the coverage ratio higher than K percent. The value of M is selected as 5 in the experiment shown in Fig. 5. The automatic annotation program employs parameters N, M and K to annotate the given image. And also generates the coverage ratio number for each tag which is assigned to the image Q. The annotated tags for the image in Fig. 5 and their coverage ratios are shown in Fig. 6. The automatic annotation program uses (3) to calculate the coverage value for each associate tag.

$$C_i = \frac{100 \times AC_i}{T} \quad (3)$$

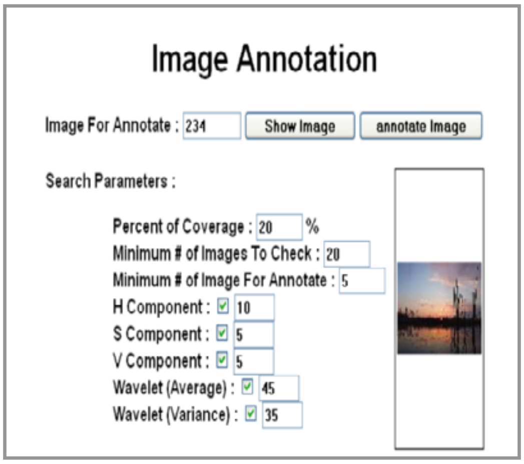


Figure 5. The UI for retrieval and annotation step

where AC_i is the average coverage ratio of the selected tag i of the M images with the value of coverage ratio higher than K% among the first N ranked retrieved images and T is the summation of the entire AC_is of the tags selected for image Q and C_i is the generated coverage number for the tag i of the annotated image.

As an example say there are assigned two tags “sky” and “water” for an image and there are three and four relevant image with “water” and “sky” tags, respectively. If the total coverage ratios in for “water” to be 108% and it is 336% for “sky”, the AC_i for “water” and “ski” will be 36% and 84%, respectively. Using (3) the coverage ratio (C_i) for “water” and “sky” tags of the un-annotated image will be 30% and 70%, respectively. The generated coverage ratios for the assigned tags by using (3) are shown in Fig. 6.

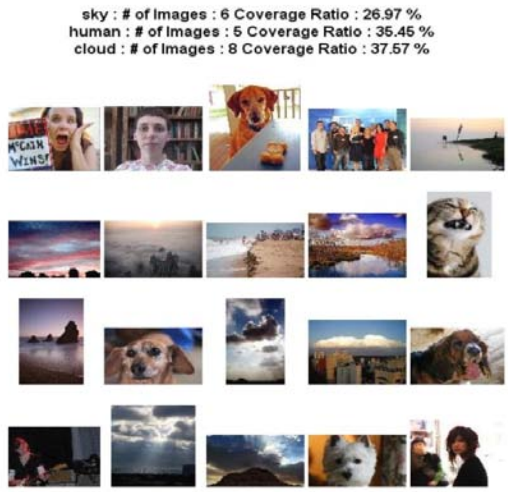


Figure 6. The retrieved images and generated tags and coverage ratio numbers for the image given in Fig. 5

III. Analysis of Experiments

A. Simulation Results

We employed flicker database [22], which includes 25000 images, in our experiments for automatic image annotation. 875 images in the database were annotated by users. The annotated images divided into two groups. First group includes 500 images and is used as reference image data based. The second group including 375 images is used as the test set. The color and texture feature vectors are generated for the entire images. We have conducted image retrieval and annotation on the test image data set using the following parameters:

Percent of Coverage: 20

Minimum # of Images to Check: 30

Minimum # of Image for Annotate: 6

H Component: 10

S Component: 5

V Component: 5

Wavelet (Average): 45

Wavelet (Variance): 35

We used precision and recall criteria to evaluate the performance of the proposed method. Precision and recall criteria are calculated as:

$$Precision = r / n \tag{4}$$

$$Recall = r / N \tag{5}$$

where r is the number of correctly annotated images for the selected tag, N is the total number of images which are labeled by the tag in the test image data set and n is the number of the images in the test image data set which are annotated by the tag. Table 1 lists the 12 tags which are used in our experiments.

We implemented the ALIP method for annotation [19] besides our proposed method. In the ALIP method [19] the user specifies a number of images as the representative for each tag or concept. The images in each tag are divided to a constant number of blocks and color and texture features are extracted for each block. LUV color space histograms and DWT are used as color and texture descriptors, respectively. A statistical model is developed for each category by using the color and texture descriptors of the blocks of the images in each category. For any given new image the image is divided to non-overlapped fixed size blocks and extracting feature descriptors is carried out. The tags which their statistical model is more similar to the descriptors are selected as the generated tags for the given image. Table 1 lists the simulation results for our method and the ALIP method [19].

We have also carried out simulations to generate coverage ratios for automatically annotated images. Table 2 indicate the difference on the coverage ratios resulted from our program by using (3) and the coverage ratios assigned to the images by the user.

B. Discussion in Simulation Results

We employed flicker database [22], which includes 25000 images, in our experiments for automatic image annotation. 875 images in the database were annotated Simulation results in Table 1 indicate that our method outperforms ALIP method in average precision and average recall by 0.1 and 0.26, respectively. This indicates that our method has produced more correct tags with larger accuracy compared to the ALIP method and hence our method is more reliable. We have also implemented the ALIP method using HSV color space instead of LUV.

Table 1. Simulation results indicating the annotation performance of the proposed method and ALIP method

		proposed method				ALIP method				improvement	
label	# of real annotate	# of annotate	# of correct annotate	percision	recall	# of annotate	# of correct annotate	percision	recall	percision	recall
flower	37	69	20	0.29	0.54	121	16	0.13	0.43	0.16	0.11
sky	93	263	81	0.31	0.87	116	32	0.28	0.34	0.03	0.53
sea	53	129	28	0.22	0.53	118	19	0.16	0.36	0.06	0.17
dog	8	135	7	0.05	0.88	109	3	0.03	0.38	0.02	0.50
human	142	146	77	0.53	0.54	116	37	0.32	0.26	0.21	0.28
tree	50	78	21	0.27	0.42	30	3	0.10	0.06	0.17	0.36
sand	33	84	13	0.15	0.39	118	12	0.10	0.36	0.05	0.03
cloud	91	237	73	0.31	0.80	120	42	0.35	0.46	-0.04	0.34
grass	47	106	32	0.30	0.68	102	12	0.12	0.26	0.18	0.43
building	76	20	5	0.25	0.07	78	8	0.10	0.11	0.15	-0.04
mountain	16	49	7	0.14	0.44	117	9	0.08	0.56	0.07	-0.13
rock	23	50	4	0.08	0.17	0	0	0.00	0.00	0.08	0.17
total	669	1366	368	0.27	0.55	1145	193	0.17	0.29	0.10	0.26

Simulation results indicate that in this case our method outperforms ALIP method by 0.11 and 0.17 in average precision and average recall, respectively. The higher performance in our proposed method is mostly due to the coverage ratio parameter which we have considered for the tags assigned to the reference images. In fact this parameter weights the various tags for the image and this makes the annotation process more reliable and effective.

The simulation results on evaluation of automatic generation of coverage ratios indicated on Table 2 indicate that the average difference on the estimated coverage ratios with the assigned values by the users is 28.99 for the correctly annotated tags. As a result the performance of the automatic generation of tags is not satisfactory and it is still an open research issue in our approach.

Table 2. Simulation results indicating the difference in the coverag ratio of the annotated images

label	# of tags correctly annotated	Average difference on coverage ratio for correct annotations	Total # of tags	Average difference on coverage ratio for the entire annotations
flower	34	33.53	82	36.73
sky	91	16.88	273	19.75
sea	48	28.82	149	23.12
dog	8	30.35	121	38.72
human	129	30.80	196	28.97
tree	48	25.58	105	25.70
sand	30	28.11	100	21.79
cloud	86	20.89	249	22.89
grass	45	21.05	119	22.19
building	72	55.76	87	50.62
mountain	16	21.11	58	21.76
rock	20	36.90	65	32.35
total	627	28.99	1604	26.93

IV. CONCLUSION

In this paper an automatic annotation method based on coverage ratio of tags by employing both image content and metadata is introduced. We have used color histogram and DWT as color and texture descriptors, respectively. Moreover, we employed the annotation produced by the user along with coverage ratio parameter for each tag in our automatic annotation method of un-annotated images. We have implemented ALIP method besides our method. The precision and recall criteria are used to evaluate the performance of automatic annotation by the two implemented methods. Simulation results indicate that our proposed method has in average superior precision and recall compared to the ALIP method. Our method has 0.26 higher average recall and 0.1 higher average precision compared to the ALIP method. Each image conveys different semantic meanings from various points of view and even the same user may infer different concepts from the same image. It makes the image annotation a user dependent process which for the same user may comes to different results according to his or her point of view. Coverage ratio can improve the annotation performance because it quantifies the extent that various concepts on image may affect the viewer who annotates the sample images. Moreover it proposes a quantitative approach in evaluating and processing different ideas about the content of an image. This is the reason why our proposed method improves image annotation performance. Hence, we can conclude our proposed automatic annotation method can be used in various image annotation applications in the image and tag based image retrieval methods. On the other hand simulation results on automatic generation of coverage ratios were not satisfactory. As a result the automatically annotated images cannot be used to expand the reference image dataset and automatic generation of coverage ratio remains an open problem in our study.

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