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Annotation based Image Retrieval System by Mining of Semantically Related User Queries with Improved Markovian Model

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Abstract

Objective: The main objective of this research is to reduce the semantic gap between human-understandable high-level semantics and machine generated low-level features for Automatic image annotation in Online Image Retrieval system. The semantic gap reduction is done by integrating the ontological concept with the Semantic annotated Markovian Semantic Indexing. **Methods:** The image annotation is the plays major task in the online image retrieval system by retrieving the user required images. In the existing system Latent Semantic Indexing (LSI) and Markovian Semantic Indexing (MSI) methodologies are used for the online image retrieval. However this work cannot retrieve the images in the accurately due to lack of semantic knowledge about the user submitted high level key words. This issue is resolved in the proposed research methodology by introducing the technique called Semantic annotated Markovian Semantic Indexing (SMSI) which is used for retrieving the images and automatically annotates the non-annotated images in the database using hidden Markov model. In contrast to traditional annotation based image retrieval system which retrieves images based on low-level features, the proposed SMSI semantically retrieves the images by searching semantically annotated images in a database for a user query. Each non-annotated image in a large collection of training samples would be annotated automatically with a posteriori probability of concepts of annotated images present in it. At last semantic retrieval of images can be done by measuring semantic similarity of annotated images in the large database by using Natural Language processing tool namely WordNet. In addition to that entity based ontology representation is introduced which tend to reduce the semantic gap between the human defined higher level keywords and machine specific lower lever features. **Results:** The presented SMSI method possess definite theoretical advantages and also to achieve better Precision versus Recall results when compared to Latent Semantic Indexing (LSI) and Markovian Semantic Indexing (MSI), methods in Annotation-Based online Image Retrieval system. The better accuracy is achieved while retrieving the contents based image annotation where the semantic gap is reduced considerably. **Conclusion:** Thus the analysis of presented work is demonstrates semantically related features of images and achieves improved retrieval result when compare with the other state-of-art techniques.

Keywords: Automatic Image Annotation, Latent Semantic Indexing, Markovian Semantic Indexing, Semantic Annotated Markovian Semantic Indexing

1. Introduction

In general, accessing of multimedia information system necessitates the capability to search and organize the information in a sequential manner. Since the availability of technology to search text in web has been increased, the result of retrieving relevant information has becoming a challenging issue.Several researchers[1] have examined methods to retrieve images with respect to their content however many of these frameworks needs the user to query based on image models like colour or texture in which users are not familiar with it. Usually, user would like to create semantic queries by employing textual descriptions and discover relevant images to those

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ofsemantic queries. Consider a query posted by user like "List all images of tigers in grass". The retrieval of images for this type of query is a quite difficult and impossible for producing relevant result with conventional image retrieval systems and therefore has not led to extensive implementation of these systems. The conventional solution to this problemused the libraries and other associations to annotate those images manually and then search those annotations. Even if humans be likely to relate images with high-level concepts, the present computer vision systems extract mostly low-level features from images and the association between low-level and high-level feature semantics of image content is lost. In general,neither a distinct low-level feature nor a group of multiple low-level features has clear semantic meaning.

Besides, the similarity measures among visual features do not essentially match perception of humans[2] and, hence, retrieval results of low-level methods are normally unsatisfactory and frequently unpredictable. This type of unprediction is often said to be the semantic gap which lacks the concurrence between the information extracted from the visual data and the understanding that the same data comprise for a user in a certaincondition. The limitation occurs is thatthe retrieval process fails because ofthe lack of semantic gap.

Annotation-Based Image Retrieval (ABIR) systems are achallenging technique which includes proficient semantic content of text based queries into image captions such as Google Image Search, Yahoo! Image Search. Older method of annotation based retrieval system uses the Latent Semantic Indexing (LSI)-based methods that were primarily employed with increased success in document indexing and retrieval, were included into the Annotation-Based Image Retrieval (ABIR) systems to determine a more reliable concept organization. Yet, the stage of achievement in these efforts is uncertain were a reason lies in the Sparsity of the per-image keyword annotation data when making assessment to the number of keywords that are generally assigned to documents.

Earlier to annotation based image retrieval system, content-based retrieval systems have been developed by Datta et al[3]. The majority of this method is based retrieving images with low level features. Particularly, this systemcan be classified into two major categories that are those that carry out semantics mining with regards to the examination of textual information related to images, namely captions; alternative (alt) text in html pages assigned keywords, annotation. Then those systems are based on the extraction of low-level visual features namely colour, texture so as tomake alignment, classification, searching and summarization in image collections. Techniques of the first category rely on difficult annotation, while the second methods typically cannot efficiently detain semantics. Moreover, a few techniques employs both low-level features in the type of visual keywords[4] by Bhattacharya et al and then uses text annotation method by Li et al. and Joshi etal.[5,6] to make content-based process but there occurs demand frequently of the general participation of users for linguistic annotation of pictures in images.

Annotation-Based Image Retrieval systems include more efficient semantic concepts which are categorized into image captions and text-based queries. A direct outcome of these methods is originally employed for document retrieval which may be appropriate for ABIR systems. Latent Semantic Indexing is presented by Berry et al. which were originally extended for document retrieval[7]. Then in Hofmannetal.[8] presents, the probabilistic Latent Semantic Indexing (pLSI) based on the Aspect Model[9] which acts as an substitute to projection (LSI) or clustering schemes for document retrieval. Latent Dirichl Allocation (LDA) was proposed by Blei et al. to address the drawbacks of PLSI considering generalization and over fitting[10]. Whereas in[11] Markov chain Monte Carlo technique is presented by Griffiths and Steyvers which is incorporated to LDA, a new probabilistic model characterizing both topics and authors in document retrieval, and later over fitting problem is these methods are resolved by using Gibbs sampling presented by Steyvers et al[12,15]. However these methods are mainly used for document retrieval schemes and the improved accuracy is not obtained for image retrieval process.

In this paper, Semantic annotated Markovian Semantic Indexing(SMSI) is proposed in which novel semantic retrieval of images is done based on Hidden Markov model based annotated images. To annotate the images, features such as Colour and texture feature are extracted by using Colour Histogram and Log-Gabourfilter methods. With the help of these extracted features, Images are annotated by using Hidden Markov model. The parameters of the model are estimated from a set of manually annotated (training) images. Each image in a large test collection is then automatically annotated with the a posteriori probability of concepts present in it.After annotating images, images are semantically retrieved based on Natural Language processing tool namely WordNet. Semantic Similarity based Image Retrieval Model is used for discovering similarities between Images in the database with the query image containing conceptually similar terms. These methods are implemented and evaluated using WordNet.

2. LSI based Image Annotation System

Latent Semantic Indexing (LSI) is an indexing and retrieval technique that applies a mathematical procedure known as Singular Value Decomposition (SVD) to recognize patterns in the association of terms and concepts enclosedin an unstructured collection of image collections. LSI is derived from the principle states that the words that are utilized in the same contexts be subject to have similar meanings. The primary feature of LSI is its capability to extracts and inherits the conceptual substance of a text body by launching associations between those terms that arise in similar contexts.

During the retrieval of images by Latent Semantic Indexing (LSI), Singular Value Decomposition (SVD) is employed to decompose the term by construction of Image matrix into three matrices as T, S and D: T, represents a term by dimension matrix, S represents a singular value matrix in dimension by dimension and D represents an image by dimension matrix.

For the LSI approach the steps in constructing the distance table is as follows:

- Perform a singular value decomposition $A = USV^T$ on keyword-image matrix A, for obtaining the required dimensionality k. As the dimensions in this research are not uses much values, the completedimensionality isused are$k = 21$ and it is reduction to $k = 10$.
- Use the standard LSI method and estimate the distance between the columns of SV^T as the cosine of their angle. This is done because that the columns of SV^T denotes the images in their LSI representation.

Consider the query q = [Greek(0.5), Islands (0.5)], as a column vector,initially it is mapped on the image space by $q = q^T US^{-1}$ and then its distance to all the images is calculated by the cosine of its angle with each column of SV^T.

LSI correlates keyword that shows at the same image and images once they are annotated with the same keyword, starting consequently from a keyword or image frequency matrix singular value decomposition offers a comactdemonstration of keywords and images in a space of less dimensions.

3. Semantic Gap Reduction using Entity based Ontological Representation

Semantic gap becomes the biggest issue in image retrieval system where there is a large gap exists between the human submitted higher level entities and the machine generated lower level entities. The accurate results cannot be retrieved where the keywords are not match semantically. For example, human higher level keyword like "Retrieve image with more grass" cannot be matched with the images which is annotated using machine's lower level entities like "'green colour', 'diamond shape'", etc.

To overcome this limitation in this work, ontological representation of higher level entities is introduced through which higher level keywords can be matched exactly. Ontology is defined as the representation of the attributes with the relationship present among them. In this work, higher level keywords are represented as ontology where the keywords are converted into intermediate level words in terms of semantic meaning which will then mapped with the lower level key words to retrieve the more accurate results.

The sample representation of entities in the ontological format is given as follows:

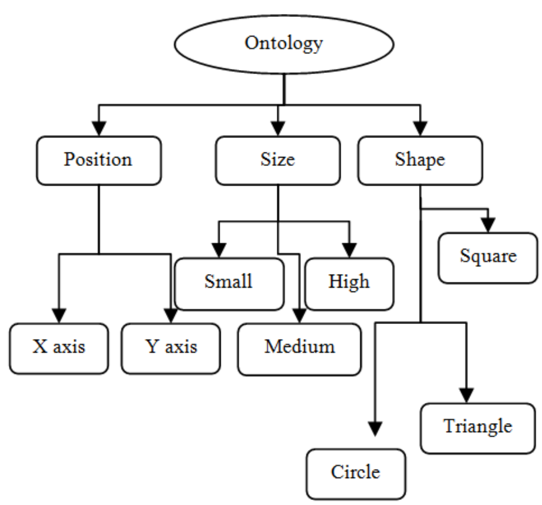

Figure 1. Entity ontology.

In the Figure 1, position size and shape are described as the intermediate level features which indicate the semantic meaning of the higher level key words directly. These intermediate words are mapped with the lower level features of images directly. Like shape of the image, colour of the image directly.

The mapping of attributes is done by calculating the attribute value and its range of value that lies. This is done by calculating the upper and lower bound of the features values. After calculation, overlapping of the higher level of keywords over the lower level features are calculated. If it is overlapped then it is said that values are matched together. If it is not matched then it can be said that the contents are not matched. This is calculated by using the following equation:

$$\int_{L_{q-1,z}}^{H_{q,z}} pdf(x_z)dx_z = \frac{1-V}{Q_z - V.(Q_z-1)}, q = 2,...Q_z$$

Where

Pdf (x_z) →probability density function of higher level keyword

V → Overlapping factor

$L_{q,z}$→Lower bound

$H_{q,z}$→ Higher bound

Q_z→Number of lower level entities

The overlapping factor is calculated by using the above equation which will compare with the defined overlapping factors. The overlapping factor is taken as 0.25 in this work. The calculated overlapping value should be less or equal to this value for semantic matching.

4. MSI Annotated Image Retrieval

In this section, the user implicitly relates the retrieved or downloaded images to the query which is submitted by the user. The goal of the Markovian chain transitions is to make use of keywords to compute logical connections among keywords. When some user relates image to the submitted query, in which each keyword follows keyword and this repeats M times, then the updation of one step transition probability is done with the method by constructing a Markov chain where each keyword matches to a state. The state counter of each keyword is advanced when each time a keyword appears in a query. Once another keyword proceeds in the same query, their interstate link counter is also parse. Both the existences of the keywords and the sequencing of this presence of keywords measured in this way. The queries relating to an image are processed by batch for this image, after that the counters are preceded, and the probabilities are updated as obtained effective results.

The correlation between the keyword and image projected in the Markovian Chain transactions are used here. Fast retrieval can be performed by clustering the keyword space into similar keywords. In this point of view, the Aggregate Markovian Chain of all the queries asked by every user despite of the selected images has been built in this stage. The kernel of this procedure is estimated analogous to the earlier step.Though a Markov kernel isused to cluster the keyword space rather than estimating an explicit probability distribution, the idea of AMC model is used for keyword relevance. Hence the optimization is performed. Then the AMC will be used to cluster the keyword space and describe precise relevance links between the keywords through this clustering.

For the MSI system, thesteps in building the distance table are as follows:

- Parse the annotated text images included in the ground-truth, allocate an index for each distinctive keyword and construct the one-step transition among keywords probability matrix PG that is the AMC, considering the annotation of each image as a query related to this image. Similarly to step 1, in order to convert the process to monodesmic, add a small quantity to all the one diagonal elements (elements lying on the superdiagonal) and subtract it from any random nonzero element in the same line.
- Perform the Eigen decomposition P_G =VDV^{-1} and calculate F_G at the desired n from the following equation.

$$f_i(n) = v_1 + \frac{\tau_i(n)}{n+1} \quad (1)$$

- Compute the zero-mean F_G^T by subtracting the mean and perform the Eigen decomposition of the covariance matrix of F_G^T *as* $\sum F_G^T = V_1 D_1 V_1^{-1}$.
- Compute $B = D_{1k} V_{1k}^{-1}$where D_{1k} is a square k × k sub matrix of D1, holding the k largest eigenvalues of $\sum F_G^T$ *and* V_{1k}^{-1} the sub matrix of the k rows of V_1^{-1} that relates to these eigenvalues.
- Estimate the reduced k-dimensional $\sum F_G^T$ *from* $\sum F_G^T = \text{cov}(B^T)$, cov denotes the covariance matrix. At this point the dimensionality of $\sum F_G^T$ is reduced by projecting on the k principal components. Then the mapping of image vectors in the same space can be performed.
- if A is the matrix containing rows of image vectors then project the image vectors in the k-dimensional space by $A_k = AV_{1k}D_{1k}^{-1}$ where V_{1k} the sub matrix of the k columns of V1 that relates to the k largest eigenvalues of $\sum F_G^T$.
- For every pair or rows r_i r_j of A_kCompute their distance by $(r_i - r_j)\sum_k F_G^T (r_i - r_j)$.

If we do not need to rise to a power, step 2 above can be omitted. This is the condition where the annotation is done with unidentified source and there is no Markovian relationship to the keyword data, in that situation MSI performs similar to LSI. The major difference between the MSI approach and LSI is that no power is used in the AMC matrix. Certainly the MSI approach uses a square keyword or keyword matrix in replace of the non square keyword or image matrix of LSI to minimize the keyword space dimensionality.

5. Semantic Annotated Markovian Indexing (SMSI) based Image Retrieval System

In this section Semantic annotated Markovian Semantic Indexing (SMSI) is used for retrieving the images and automatically annotates the images in the database using hidden Markov model. Initially features of Colour and texture feature are extracted by using Colour Histogram[13] and log Gabor filter methods[14]. With the help of these extracted features, images are annotated and updated by using Hidden Markov model.

5.1 HMM based Image Database Updation

HMM, provides

- Compute the model parameters from annotated imageand caption pairs.
- Aligning regions of image with caption words in an image and caption pairs, and
- Estimate the likelihood of a caption-word being exist in an image.

Assume a collection of image and caption pairs be given and consider the effect of developing a stochastic generative model that describes each pair together.

Let I = $<i_1 \dots i_t>$indicate segments or regions in an image, and C = {c(1). . . c (n)} represents the objects or concepts present in that image, as defined by the equivalent label or caption C. For each image region i_t, t = 1. . . T, Assume $x_t \in IR^d$ denotes the colour, texture, of the region. At last, let V refers to the global vocabulary of the caption-words $c_n$throughout theoverall collection of images.

This framework models the $\{x_t\}$ - vectors of an image I as a hidden Markov process, created by an unobserved Markov chain whose states $s_t$gets values which is incaption C. Particularly, each x_t is produced in proportion to probability density function $f(\cdot|s_t)$ specified the state s_t, where s_t itself is a Markov chain with a well-known initial state s_0 and transition probabilities $p(s_t|s_{t-1})$.

The state sequence is as follows:

$$f(x_1,\dots,x_T,s_1,\dots\dots s_T\ |s_0)=\Pi_{t=1}^{T} f(x_t|s_t)p(s_t|s_{t-1}) \tag{2}$$

As this level of detail is generally not given in a caption, a Hidden Markov Model (HMM) is asuitableapproach for estimating the joint likelihood as follows:

$$f(x_1^T,C|s_0)=\sum_{s_1^T\in C^t}\sum_{t=1}^{T}[f(x_t|s_t\ )p(s_t]|s_{t-1}) \tag{3}$$

where X_i^T denotes the T-length sequence <x1, .., xT>.

This section retrieves the annotated images semantically based on NLP. Image retrieval based on Semantic similarity implies discovering semantically similar terms by means of term taxonomies by using WordNet. The following step describes the working of Semantic annotated Markovian Semantic Indexing (SMSI) is as follows:

5.1.1 SMSI (Semantic annotated Markovian Semantic Indexing)

- Construct the ontology for the entities submitted by humans.
- Convert the higher level key words into intermediate level words by extracting in depth meaning.
- The user relates the semantically retrieved or downloaded images to their specified query.
- Consider Markovian chain transitions in the order of the keywords the aim of the proposed approach is to quantify logical connections between original keyword as well as semantically matched keywords for the original keyword.
- Consider the Input image I and Query Q in which Query consist of number of keywords K1, K2 and K3 etc.
- Obtain the semantically meaningful keyword for the Keywords for the Original Query by using Natural Language processing tool of Wordnet.
- Relate Image I to the Query of original keywords with semantically obtained keyword for m times of iterations by using Markov chain transition.
- Construct and Update transition probability $P_i(k_i, k_j)$ as follows

$$P_i(k_i,k_j)=\frac{Npi(ki\bigcup_{i=1}^{n}Sk_i,kj\bigcup_{i=1}^{n}Sk_j)+m}{N+m} \tag{4}$$

Where N= M * n(S_k)
P_i(k_i, k_j) is the transition probability.
k_i, k_j denotes keywords in Query.
M is the number of original keywords in Query.
N is the number of keywords associated with semantically obtained keywords.
S_k is the semantically obtained keyword for the original keyword in Query.

If P_i(k_i, k_j) is the current probability (before the update) based on N keywords then the new probability (based on N + m keywords) is calculated by the recurrent formula.This procedure builds a Markov chain in which each keyword with its semantic keywords relatesto a state. When a keyword appears in query, its state counter is preceded; when another keyword goes afters in the same query, their interstate link counter is also parsed.

- In this step, the Aggregate Markovian Chain is built-forevery query with its associated keywords required by users regardless of the selected images.
- Optimization step: The AMC will be used to cluster the semantically attained keyword space and describe explicit relevance links between the semantically obtained keywords through this clustering.

6. Experimental Result

6.1 Dataset Description: Real Time Dataset

We used the real time dataset with 1,109 images above, in 20 classes of about 50 images in each class, annotated with a total of 437 keywords, each annotation being a text string of up to 25 keywords. We use this data set to do the comparison by means of Precision versus Recall diagrams.

6.2 Performance Matrices

The proposed method is compared with the Markovian Semantic Indexing. Comparison with MSI and HMM in the application area of Annotation-Based Image Retrieval with Precision versus Recall diagrams on ground truth databases reveal that the proposed approach achieves better retrieval scores.

6.2.1 Precision

The precision rate is defined as the ratio of the number of relevant images retrieved and total number of images in the collection.

$$\text{Precision} = \frac{|\{\text{relevant images}\} \cap \{\text{retrieved images}\}|}{|\{\text{retrieved images}\}|}$$

6.2.2 Recall

Recall rate is defined as the ratio of number of relevant images retrieved and to the total number of relevant images in the collection.

$$\text{Recall} = \frac{|\{\text{relevant images}\} \cap \{\text{retrieved images}\}|}{|\{\text{relevant images}\}|}$$

6.2.3 Accuracy

Accuracy is defined as the degrees of reduced misclassification error rate in terms of classifying different number of features present in the environment. Accuracy of the proposed research work should be more in the proposed research work in terms of reduced misclassification error rate than the existing approach. Accuracy is evaluated as,

$$\text{Accuracy} = \frac{(\text{True positive} + \text{True negative})}{(\text{True positive} + \text{True negative} + @\text{False positive} + \text{False negative})}$$

The following comparison table shows the values obtained for existing and proposed system as follows:

Table 1. Experimental result of LSI(Latent Semantic Indexing), MSI (Markovian Semantic Indexing) and SMSI (Semantic annotated Markovian Semantic Indexing)

Algorithm	Precision in %	Recall in %
LSI	25.00	33.33
MSI	33.33	81.00
SMSI	83.33	98.00

Table 2. Experimental result of the LSI, MSI and SMSI

Method	LSI	MSI	SMSI
Accuracy in %	38	56	78

The experimental results for proposed system are plotted on graphs based on these formulas. The graphs shown in the figures below give better analysis perspective on the Automatic annotated online image retrieval task.

The above graph in Figure 2 compare the Precision-Recall parameter between LSI(Latent Semantic Indexing), MSI (Markovian Semantic Indexing) and SMSI (Semantic annotated Markovian Semantic Indexing). These measures are mathematically calculated by using formula. This graph shows the Precision-Recall rate of LSI(Latent Semantic Indexing), MSI(Markovian Semantic Indexing) and SMSI (Semantic annotated Markovian Semantic Indexing). In this graph X-axis will be methods such as LSI (Latent Semantic Indexing), MSI(Markovian Semantic Indexing) and SMSI (Semantic annotated Markovian Semantic Indexing)and Y-axis will be Precision-Recall rate. From the graph can see that, Precision-Recall of the system is reduced somewhat in LSI (Latent Semantic Indexing), MSI (Markovian Semantic Indexing) than the SMSI (Semantic annotated Markovian Semantic Indexing). From this graph can say that the Precision-Recall rate of SMSI (Semantic annotated Markovian Semantic Indexing) is increased which will be the best one.

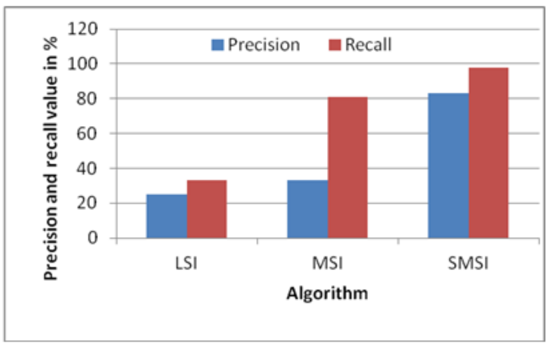

Figure 2. Precision-Recall comparison graphs.

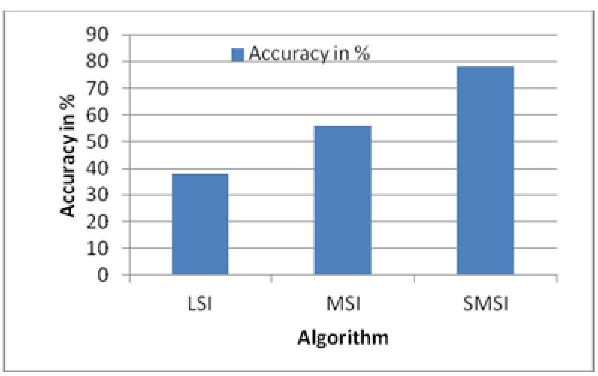

Figure 3. Accuracy comparison graph.

The above graph in Figure 3 compare the Accuracy parameter between Latent Semantic Indexing (LSI), Markovian Semantic Indexing (MSI) and Semantic annotated Markovian Semantic Indexing (SMSI). These measures are mathematically calculated by using formula. In this graph X-axis will be methods such as LSI, MSI, SMSI and Y-axis will be Precision-Recall rate. From the graph can see that, accuracy of the system is reduced somewhat in LSI and MSI than SMSI. From this graph can say that the accuracy rate of SMSI is increased which will be the best one.

7. Conclusion

The present work proposes Semantic annotated Markovian Semantic Indexing (SMSI) a novel semantic retrieval of images is done based on Hidden Markov Model (HMM) based annotated images. Features of colour and texture are extracted by using colour Histogram approach and Log Gabor filter model. Automatic annotation of images in database has been done by using a proposed Hidden Markov Model which uses the extracted features where all states represent the concepts. Semantic gap is reduced considerably by representing the human submitted keywords in the ontological format. This is done by mapping the higher level values into intermediate values based in the sematic meaning. Semantic similarity based image retrieval can be done with the use of Natural language processing tool namely WordNet where conceptual similarity between natural language terms were done. Comparative analysis of proposed Semantic annotated Markovian Semantic Indexing (SMSI) has been done with the LSI annotated image retrieval and MSI annotated image retrieval. Experimental results of Precision versus Recall for the proposed system achieves better scores than LSI and MSI scores of result. The present research is open for future research challenges and the ultimate goal of image annotation is to process tens of thousands of images of various concepts precisely and efficiently, not a single query case. The present works retrieves images efficiently and still takes large time to process in large collection of databases. Hence incorporation of advanced indexing or hashing technique can be explored for further research.

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