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A New Methodology for Automatic Annotations of Images

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ABSTRACT: This paper shows brief description about the Markovian Semantic Indexing approach. The existing system uses the Latent Semantic indexing or Probabilistic Latent Semantic Index model. With this LSI having problems like when using large scale collection of images causes in low performance and speed levels and the PLSI approach also has problems like it is incomplete since provide no probabilistic model at the level of documents, leads to over fitting problems if there are too many parameters in the model and it's not clear how to assign and how to assign probability to a document outside of the training data. In the context of online image retrieval system a new approach has been introduced called Markovian Semantic Index. This model is useful when annotation data per image having large training set data and suitable particularly in the context of online image retrieval systems.

KEYWORDS: Latent Semantic indexing, Probabilistic Latent Semantic Index model, Markovian Semantic Index

I. INTRODUCTION

Annotation based image retrieval systems are an attempt to incorporate the more efficient semantic content into both text based quires and image captions. Initially Latent Semantic Indexing (LSI) [1] is a document retrieval technique which addresses the some of the shortcomings inherent in traditional lexical matching techniques. LSI deals with the problems of synonymy i.e. many words refer to same object and polysemous i.e. many words have multiple meanings. This approach tries to search that is closer to representing the underlying semantics of a document, rather than just by matching specific keywords. This approach starts with the creation of terms by document matrix. This high dimensional matrix is further decomposed into a reduced dimension matrix called Singular Value Decomposition (SVD) [1]. This decomposition is done to filters out the noise in a document. This LSI has some problems like decomposed matrix are difficult to interpret, this decomposition is computationally expensive and when using large scale collection of images causes in low performance and speed levels. To overcome these drawbacks a new and alternative approach to LSI model was developed, which called Probabilistic Latent Semantic Index (PLSI) [1]. This approach also deals with synonyms and polysemous of words. This is an automated document indexing in this each document represented by its document indexing by words frequency. The latent variable model is a model which latent variables are associated with observed variables which follow by this PLSI. It has a more robust statistical foundation, and is able to provide a proper generative data model. This PLSI model has problems such as it is incomplete since provide no probabilistic model at the level of documents, leads to over fitting problems if there are too many parameters in the model and it's not clear how to assign and how to assign probability to a document outside of the training data. To overcome the limitations of this PLSI a new approach proposed called Markovian Semantic Index. It is proposed in the context of online image retrieval system. The MSI is useful when annotation data per image having large training set data and suitable particularly in the context of online image retrieval systems Because of this method delivers the better and efficient results. When there is a lot of correct, compared to different systems that of non-dynamic or non-adaptive nature to outline keyword connection. MSI achieves higher retrieval ends up in sparsely annotated image knowledge sets. This MSI provides benefits in retrieving pictures with deeper dependencies than easy keyword co occurrence.

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Aggregate Markov Chain AMC frame work is used to build relevance between keywords identified and queries used to automatically annotate the images. Raftopoulos et al introduced a novel probabilistic approach for automatic annotation, indexing and annotation-based retrieval of images called Markovian semantic Index. The MSI is useful when annotation data per image having large training set data and suitable particularly in the context of online image retrieval systems. In this MSI some Geometric interpretations of the proposed distance are provided and its relation to a clustering in the keyword space is investigated. By means of a new measure of Markovian state similarity, the mean first cross passage time (CPT) [1], optimality properties of the proposed distance are proved. Images are modeled as points in a vector space and their similarity is measured with MSI. This MSI method possess certain theoretical advantages and to achieve better Precision versus Recall results. The precision rate is defined as the ratio of the number of relevant images retrieved and total number of images in the collection.

$$P = \frac{number\ of\ relevant\ images\ retrieved}{total\ number\ of\ images\ returned}$$

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

$$R = \frac{number\ of\ relevant\ images\ retrieved}{total\ number\ of\ relevant\ images\ in\ the\ databas}$$

II. RELATED WORK

Image annotation and retrieval is most popular research area for decades [6]. The most popular approach for image retrieval is Content Based Image Retrieval (CBIR). In this CBIR systems use an image as the input query. By this faces some problem called semantic gap by the use of low-level features for similarity matching which reduces the performance of the image retrieval. This CBIR is based on image low level features like color, shape, or texture. This method fails to meet user expectation. The main factor is the semantic gap. Semantic gap is a gap between high level information semantic (keyword, text descriptor, etc.,) and results of low level features extraction (color, shape, etc.,). This problem is crucial because high level information semantic is meaningful and effective for image retrieval. To overcome the problems raised due this CBIR approach,

A new image annotation method known as Annotation Based Image Retrieval (ABIR) has been developed. This ABIR could achieve the performance, which is two times better than the CBIR systems in reducing the semantic problem. The below figure shows one possible integrated system architecture. In the above figure there are different databases such as image collection, visual features and text annotation. In image collection database holds the raw images for visual display. The visual feature database stores the visual features extracted from the images using feature extraction techniques. The text annotation database contains the key words and free-text descriptions of the images retrieval is not a replacement of, but rather a complementary component to the text-based image retrieval.

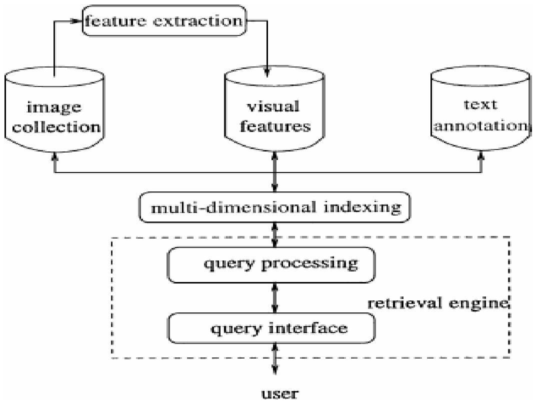

Fig.1 Image retrieval system architecture

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This architecture has the two major characteristics of this system architecture. One is its multi-discipline and inter-discipline nature. The main step in ABIR [2] is partitioned into two parts one is automatic image annotation and query processing Automatic image annotation can be starts by doing image segmentation based on low level feature image and assigning label to each segmentation generated. One of approach for this automatic image annotation is using machine learning techniques. These are commonly used for the image classification and image feature analysis such as segmentation etc. In this image annotation method, a general term is usually called 'blob'. A blob is a part of an image with a vocabulary meaning. The image is separated into blobs based on the region or cluster and the corresponding blobs are labeled with a word.

III. PROPOSED SYSTEM

Markov chain based image indexing (MSI) has been used in the context of online image retrieval system. User queries are considered to construct an Aggregate Markov Chain (AMC) through which the relevance between the keywords obtained by the system. The inference engine [12] of the Markov chain based image indexing approach lies in the clustering of the state space, because this clustering organizes the states into collections of relevance. In terms of scalability, the degree of this clustering has been examined according to the size of the system. The clustering state degree in Markov Chains has been systematically studied, referred as the coupling degree. This degree quantifies the degree of state clustering in the chain and this can be assumed in terms of state connectivity. The Markov Chain based approach for online image retrieval system [1]; this is most efficient in terms of precision and recall rates. This mainly based on the concepts of use queries mining using Markovian Chain mode.

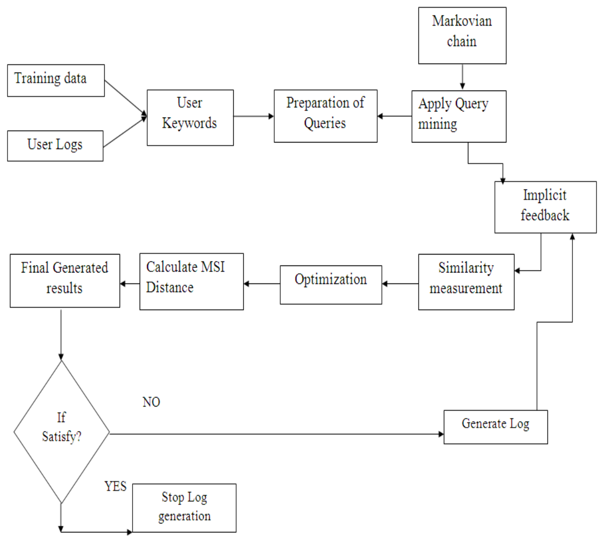

Fig2. Relevance Feedback methods

Based on this measurement an Aggregate Markov Chain (AMC) Optimization technique will be applied. In the next step calculates MSI distance and generates the result. Based on the user satisfaction the relevance implicit feedback will be generated. Here, identified that the limitation of this approach is in terms of end user satisfaction It is giving the better performances against the existing one, in this project we are to proposed and extend the existing method of online image retrieval by using the concept of Relevance Feedback methods. We use implicit and explicit feedback method along with Markov model based online image retrieval system. This method is more efficient, robust as well as reliable. In real time applications need to have automatic image annotation by using the appropriate input keywords as well as the concept of relevance feedback to satisfy the end user needs. Hence the Markov chain based

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method for online image retrieval further extended to help the users identify the images that are most satisfied as per their need [6]. This improves the performance of proposed system in terms of efficiency and robustness.

Similarity measure

In the proposed system need a connectivity measure between the Markovian states which will serve as probabilistic relevance link between the keywords. In the above figure.3 the states 1 and 2 being isolated from each other but identical as far as the process is concerned after starting from these states, here can't define any metric that involves directly these two states, like the first passage time, since the two states are isolated with each other and a passage between them does not exist.

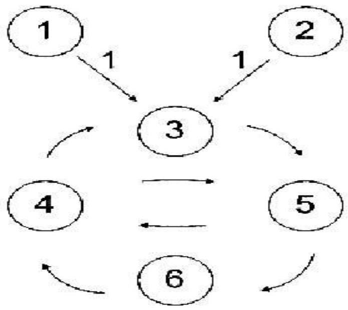

Fig.3 A Markov chain showing two nonrecurring states with identical future.

Next we need to compare these two states having connectivity with other states. For this comparison use a measure state similarity called Mean First Cross Passage time (CPT). [6] Here we calculate the mean first cross passage time between any two states X and Y will measure the difference between these two states with other states. Due to the memory less property, once the process reach the same state, let's say Z, from X and from Y then the different initial condition has no effect for the process anymore, So the Mean First Cross Passage time between two states will be the expected time it takes for the process to cancel out the fact of one of these two states being the initial condition rather than the other. Intuitively, the CPT will be large between states that there is no state to which both of them connect with short passages [1]. The CPT is calculated next. Choose an arbitrary state Z. If the first passage crossing from X and from Y happened at Z then the process from X visited Z for the first time after an average of θ_{XZ} transitions and the process from Y also visited k for the first time after an average of θ_{YZ} transitions. The difference of the mean first passage times of X and Y to k is the expected time Z will have to wait for the second passage after it was visited by the first passage and this is the CPT given that the first crossing of passages happened at state Z. To say this formally, if X; Y arbitrary and Z recurrent and the mean first passage time from X to Z and from Y to Z is θXZ and θYZ, respectively, then the mean first cross passage time between X and Y given that the first crossing of passages will happen at state Z is $|\theta_{XZ} - \theta_{YZ}|$ To overcome the problem of nonrecurring states and to also remove the condition that the first crossing of passages will happen at state Z.

Aggregate Markovian Chain

The Aggregate Markovian Chain [12] approach is used to cluster the keyword space and define explicit relevance links between the keywords by means of this clustering. This clustering task is linked to the convergence characteristics of the AMC chain by evaluating the series

$$FG(n) = \sum_{k=0}^{n} P_G^k$$

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Where PG is the AMC kernel. A suitable termination condition stops the series at the desired n where the slow convergence has taken over, but not before the rapid convergence has finished. The value of the determinant of $FG(n)$ is used as a termination condition since the clusters in the rows of $FG(n)$ will drop its rank and the determinant will become close to zero. $FG(n)$ is the n-step expected occupancies matrix. An optimization task is related to this procedure with respect to the total variance of the columns of $FG(n)$, when projected on the direction of the eigenvectors of PG.

IV. EXPERIMENTAL RESULTS

The proposed method MSI compared with the LSI AND PLSI in the area of Annotation-Based Image Retrieval with Precision versus Recall diagrams on ground truth databases reveal that the proposed approach achieves better retrieval scores.

V. CONCLUSION

This paper describes about the indexing methods which is an extension of the LSI and PLSI where as the LSI and PLSI having the problems when a having large set of data to be search, which makes the image retrieval system to be low performance. The proposed approach MSI improves the performance of the online image retrieval system. But there is a problem those are associated with this method which is related to end users satisfaction.

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