

# A Systematic Cross Modal Multimedia Retrieval Using Maui Indexing Algorithm

J.Merlin, R.Umesh

**Abstract**— During the searching the text data with a text queries are retrieved and image data with image queries. So, basically data searching by corresponding queries. We used the cross model-cross correlation which is retrieved the data text queries to image data and this type of cross data is retrieved. Previously we used the three algorithms for searching that is content modality (CM), semantic modality and semantic content modality (SCM). These algorithms are search small amount of dataset or database. Content modality search straight for content only; semantic modularity is store frequent query for searching and semantic content modality is combined the techniques of both. Whenever use this algorithm it retrieves only the minimum amount of data. To overcome this drawback we propose the efficient algorithm for searching that is MAUI indexing algorithm. This is a clustering approach. This type of data is form like a cluster. First we retrieved the cluster formation from a list of queries and after retrieve dataset or database of specific cluster. This algorithm is implemented by the scalable database to produce accurate results. It is avoids time computations for searching and efficiently and it is consistent to handle the huge amount of data.

**Key Words**- MAUI,SCM

## I. INTRODUCTION

In order to improve the retrieval accuracy of content-based image retrieval systems, research focus has been shifted from designing sophisticated low-level feature extraction algorithms to reducing the ‘semantic gap’ between the visual features and the richness of human semantics. This paper attempts to provide a comprehensive survey of the recent technical achievements in high-level semantic-based image retrieval. Major recent publications are included in this survey covering different aspects of the research in this area, including low-level image feature extraction, similarity measurement, and deriving high-level semantic features. We identify five major categories of the state-of-the-art techniques in narrowing down the ‘semantic gap’: (1) using object ontology to define high-level concepts; (2) using machine learning methods to associate low-level features with query concepts; (3) using relevance feedback to learn users’ intention; (4) generating semantic template to support high-level image retrieval; (5) fusing the evidences from HTML text and the visual content of images for WWW image retrieval. In addition, some other related issues such as image test bed and retrieval performance evaluation are also

discussed. Finally, based on existing technology and the demand from real-world applications, a few promising future research directions are suggested.

Multimodality is an inter-disciplinary approach that understands communication and representation to be more than about language. It has been developed over the past decade to systematically address much-debated questions about changes in society, for instance in relation to new media and technologies. Multimodal approaches have provided concepts, methods and a framework for the collection and analysis of visual, aural, embodied, and spatial aspects of interaction and environments, and the relationships between these three interconnected theoretical assumptions underpin multimodality.

Multimodal research makes a significant contribution to research methods for the collection and analysis of digital data and environments within social research. It provides novel methods for the collection and analysis of types of visual data, video data and innovative methods of multimodal transcription and digital data management.

Research on multimedia information retrieval (MIR) has witnessed a booming interest during the last five years or so. A prominent feature of this research trend is its simultaneous but independent materialization within several fields of computer science. The resulting richness of paradigms, methods and systems that has occurred as a result may, on the long run, result in a fragmentation of efforts prone to slow down progress. The primary goal of this study is to promote an integration of methods and techniques for MIR by contributing a conceptual model which places in a unified and coherent perspective the many efforts and results that are being produced under the label of MIR. The model offers a retrieval capability that spans two media, text and images, but also several dimensions: form, content and structure.

Semantic-Based retrieval has been one of the long-term goals of multimedia computing. Traditional content-based approaches for deriving semantics, purely based on low-level features, such as color and texture, have shown their limitations in conquering the so-called “semantic gap.” Modern approaches enable a semantic search by pooling a set of concept detectors (e.g., car and building) to extract semantics from low-level features, and thus forming a semantic space to facilitate high-level understanding of user queries. A search list is then produced by ranking items (e.g., shots) according to their signal responses to the selected concept detectors.

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Under the concept-based retrieval framework an apparent issue is that, given a concept detector set, mapping ambiguity between queries and concepts needs to be carefully resolved. Consider, for instance, a query of "Find shots with snow", and a concept set with three detectors: Landscape, soccer, fire. The concept similarities between snow, landscape snow, soccer and snow, fire need to be properly reasoned in order to assign the best possible detectors with appropriate weights to answer the query.

The problem of cross-modal retrieval from multimedia repositories is considered. This problem addresses the design of retrieval systems that support queries across content modalities, for example, using an image to search for texts. A mathematical formulation is proposed, equating the design of cross-modal retrieval systems to that of isomorphic feature spaces for different content modalities. Two hypotheses are then investigated regarding the fundamental attributes of these spaces. The first is that low-level cross-modal correlations should be accounted for. The second is that the space should enable semantic abstraction. Three new solutions to the cross-modal retrieval problem are then derived from these hypotheses: correlation matching (CM), an unsupervised method which models cross-modal correlations, semantic matching (SM), a supervised technique that relies on semantic representation, and semantic correlation matching (SCM), which combines both. An extensive evaluation of retrieval performance is conducted to test the validity of the hypotheses. All approaches are shown successful for text retrieval in response to image queries and vice versa. It is concluded that both hypotheses hold, in a complementary form, although evidence in favor of the abstraction hypothesis is stronger than that for correlation

## II. LITERATURE SURVEY

*Image Retrieval: Ideas, Influences, and Trends of the New Age:*

We have witnessed great interest and a wealth of promise in content-based image retrieval as an emerging technology. While the last decade laid foundation to such promise, it also paved the way for a large number of new techniques and systems, got many new people involved, and triggered stronger association of weakly related fields.

*Web News Categorization Using a Cross-Media Document Graph:*

The novelties and contributions of the proposed framework are: (1) support of heterogeneous types of multimedia documents; (2) a document graph representation method; and (3) the computation of cross media.

*Annotation and Retrieval of Music and Sound Effects:*

We use this data to train a Gaussian mixture model (GMM) over an audio feature space. We estimate the parameters of the model using the weighted mixture hierarchies expectation maximization algorithm.

*Automatic Generation of Social Tags for Music Recommendation:*

Automatic tags (or "autotags") furnish information about music that is otherwise untagged or poorly tagged, allowing for insertion of previously unheard music into a social recommender. This avoids the "cold-start problem" common in such systems.

## III. EXISTING SYSTEM

In existing system, three different algorithms are used for image retrieve. The algorithms are CM (Content Modality), SM (Semantic Modality), and SCM (Semantic Content Modality). The design of correlation mapping requires the combination of dimensionality reduction and some measure of correlation between the text and image modalities. Cross model retrieval of multimedia is a responsible for queries. Text queries are retrieved image content in huge amount. To implement some algorithm content modality, semantic modality and semantic content modality is does not satisfy for the retrieval of multimedia data to be use. There are only retrieve the small amount of data and it is inconvenient to use by large amount of data. Inaccuracy of data is provides from searching and efficiency is less to search the dataset are database.

In cross model retrieval is inconsistent to use image queries. Because, it retrieved non-related content to searching and text queries to retrieved different queries content. Huge amount of contents is retrieve form the query. Low level features are extracting from the queries. It does not support to derived large dataset and database.

## IV. PROPOSED SYSTEM

The new system is proposed to overcome the problems that are presented in the existing system. In our proposed we used Maui indexing to solve the existing problems. This algorithm is based on cluster method. In existing system, CM, SM and SCM are used for image retrieval. These existing methods are not efficient to handle large amounts of data. The pervious algorithm is inefficient to used in our proposed system; we retrieve the image by giving another related image. The user gives one image, and then the related images of that image are displayed by our proposed Maui indexing. So the user can easily get the result within a limited period of time. . List of clusters we send the user and user's to choose the clusters to retrieves content. Thus we use algorithm retrieve large amount of dataset or database. Image and text both type of retrievals is efficiently and consistence to be use.

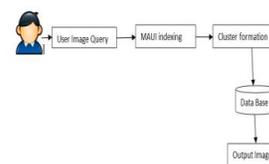


Fig.4.1. System Architecture

MODULES:

- 1) search
- 2) Indexing
- 3) Cluster formation
- 4) Retrieval

A. Search

The searching is the first module of our proposed system. This searching process is used when the user wants to search the content which is retrieved from the dataset or database. If the user enters the queries for searching then the user queries are searching their corresponding data from the database by using this query.

Basically, the query may be represented by both text and image for searching the content. After the retrieval of content the indexing is performed. Search by image works best when the image is likely to show up in other places on the web. So you'll get more results for our searching process.

B. Indexing

The indexing process is performed after the content retrieval process. MAUI indexing algorithm is to be use for searching the queries like a text or image retrieval content. MAUI automatically identifies main topics in text documents. Depending on the task, topics are tags, keywords, key phrases, vocabulary terms, descriptors, and index terms. An index is a copy of select columns of data from a table that can be searched very efficiently. Creating an index on a field in a table creates another data structure which holds the field value, and pointer to the record it relates to.

C. Cluster Formation

Clustering techniques can be applied on web search result. In case of hierarchical Approach; there is tradeoff between quick result and good quality result. Since web search result Clustering is an online process, time can't be traded. Contents are form in cluster the users are easy to access. The cluster formation process takes multiple nodes (currently 3, 4, 6 or 8) and logically bonds them together to act as a single coordinated system. Once a cluster is formed, it can be managed as a single system and all resources attached to each node are aggregated into a single managed pool of storage and compute resources.

D. Retrieval

The retrieval of content is the final stage of our proposed module. Queries are the primary forms of the retrieved data from a database. Large amount of dataset and database are retrieved from the cluster formation. These contents are consistence to one another and retrieve contents are accurate to be use. The performance of derived content is most efficient to the previous algorithm. Searching time is very low when compared with the pervious searching algorithm.

V. IMPLEMENTATIONS AND RESULT

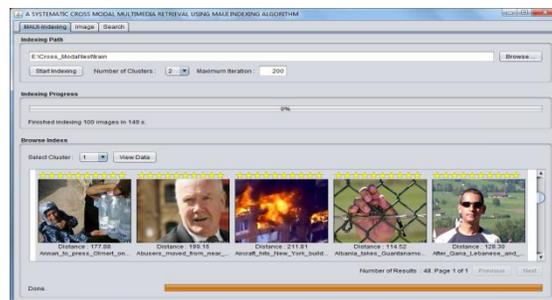


Fig.5.1. Image Indexing

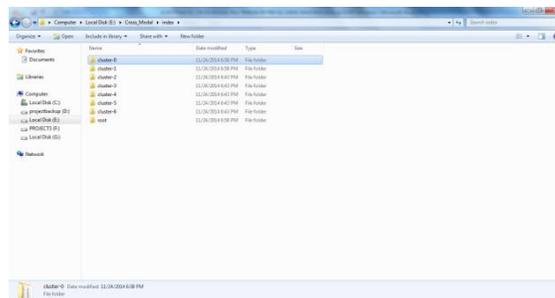


Fig 5.2.Cluster Formation

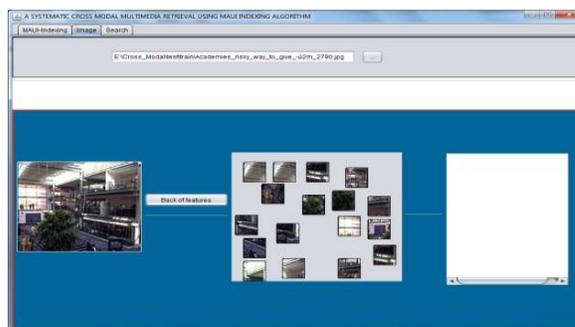


Fig 5.3. Clustered Images

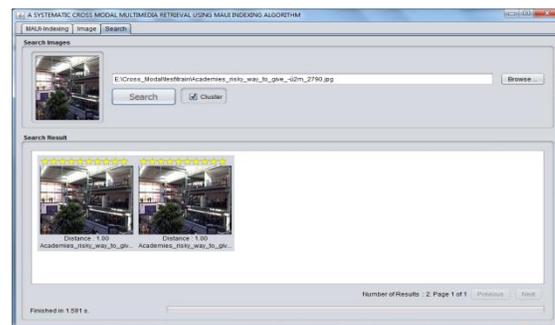


Fig5.4. Resulting Image

VI. CONCLUSION AND FUTURE ENHANCEMENT

In this paper we proposed MAUI indexing algorithm to improve the performance of queries. Cross model content retrievals does not satisfied the user requirements. Our proposed algorithm is first classified the content in cluster form and users to wants select cluster for retrieval. It is satisfied both images and text type of queries. It supports

accurate content retrieve for large dataset and database. Our proposed system van increase the availability of dataset to be search and high efficient of data can be retrieve by the indexing process.

Maui's scheduling behavior can be constrained by way of throttling policies, policies which limit the total quantity of resources available to a given credential at any given moment. The resources constrained include things such as processors, jobs, nodes, and memory. For example, a site may choose to set a throttling policy limiting the maximum number of jobs running simultaneously Per user to 3 and set another policy limiting the group, staff, to only using a total of 32 processors at a time. Maui allows both *hard* and *soft* throttling policy limits to be set. Soft limits are more constraining than hard limits. Each iteration, Maui attempts to schedule all possible jobs according to soft policy constraints. If idle resources remain, Maui will re-evaluate its queue and attempt to run jobs which meet the less constraining hard policies.

#### REFERENCES

- [1] Doyle.G and C. Elkan, 2009 "Accounting for Word Burstiness in Topic Models," Proc. ACM Int'l Conf. Machine Learning, pp. 281-288.
- [2] Escalante.H , C. He'rnandez, L. Sucar, and M. Montes, 2008 "Late Fusion of Heterogeneous Methods for Multimedia Image Retrieval," Proc.ACM Int'l Conf. Multimedia Information Retrieval, pp. 172-179.
- [3] Meadow.C , B. Boyce, D. Kraft, and C. Barry, 2007 "Text Information Retrieval Systems. Emerald Group".
- [4] Monay.F and D. Gatica-Perez, Oct.2007 "Modeling Semantic Aspects for Cross-Media Image Indexing," IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 29, no. 10, pp. 1802-1817.
- [5] Paramita.M , M. Sanderson, and P. Clough, 2010 "Diversity in Photo Retrieval: Overview of the ImageCLEF 2009 Photo Task," Multilingual Information Access Evaluation: Multimedia Experiments, pp. 45-59, Springer.
- [6] Pereira J.C and N. Vasconcelos, 2010 "On the Regularization of Image Semantics by Modal Expansion," Proc. IEEE Conf. Computer Vision on Pattern Recognition, pp. 3093-3099.
- [7] Pham.T, N. Maillot, J. Lim, and J. Chevallet, 2007 "Latent Semantic Fusion Model for Image Retrieval and Annotation," Proc. ACM Int'l Conf. Information and Knowledge Management, pp. 439-444.
- [8] Rashtchian.C, P. Young, M. Hodosh, and J. Hockenmaier, 2010 "Collecting Image Annotations Using Amazon's Mechanical Turk," Proc. NAACL HLT Workshop Creating Speech and Language Data with Amazon's Mechanical Turk, pp. 139-147.
- [9] Vasconcelos.N, July 2007 "From Pixels to Semantic Spaces: Advances in Content-Based Image Retrieval," IEEE Trans. Computers, vol. 40, no. 7, pp. 20-26.
- [10] Wang.G, D. Hoiem, and D. Forsyth, 2009 "Building Text Features for Object Image Classification," Proc. IEEE Conf. Computer Vision on Pattern Recognition, pp. 1367-1374.