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A Relative Study to Compare Image Annotation using Ontology for Semantic Web

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Abstract:

Technology plays a vital role in inventions such as photography and television, and facilitates the capturing and communication of image data. The progression of multimedia technology solicits the users thrust in various fields such as medicine, journalism, advertising, design, education and entertainment. The challenge of finding a desired picture in a wide and diverse set was one of the key issues they highlighted. Users in many professional fields are exploiting the opportunities offered, the ability to access and manipulate remotely-stored images using exciting methods. However, the process of locating a desired image in a large and varied collection can be a source of considerable frustration. The problems of image retrieval are becoming widely recognized, and the search for solutions is the active area for research and development. Content Based Image Retrieval searches the given image from set of images by using efficient image descriptors. Relevance feedback was incorporated into CBIR to make it more beneficial. However, for large and high dimensional image databases, it is obvious that the current retrieval techniques are unable to produce proper milestones for image retrieval. The main focus of this paper is to analyze the various image retrieval systems and to optimize the searching technique. In the proposed technique the images are categorized based on concepts in various domains. This paper deals with comprehensive survey of the technical achievements in the research area of image retrieval, especially content-based image retrieval, semantic image retrieval and ontology techniques which is playing a active role in current scenario.

Keywords – Ontology, Semantic web, Image retrieval, SPARQL, RDF.

I. INTRODUCTION

The rapid growth in digital image collections paves way for various multimedia databases. A huge amount of information in databases cannot be accessed or make use of the information unless it is organized to
allow efficient browsing, searching, and retrieval. The evolution on image search was traced back to the late 1970s. A very popular framework of image retrieval was proposed to first annotate the images by text and use text-based database management systems (DBMS) to perform image retrieval. The advancements such as data modeling, multidimensional indexing, and query evaluation, came into its existence along this research direction. It's very difficult to handle large image collections for two reasons. Manual image annotation and labeling requires more labor and very expensive as well as time consuming process [1]. The other difficulty results from the rich content in the images and the subjectivity of human perception. The development of image retrieval techniques depicted content-based image retrieval to overcome the huddles in text based image retrieval. Images will be indexed by their own visual content, such as colour and texture, rather than being manually annotated by text-based key words. Content-based image retrieval

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(CBIR) plays a vital role in image retrieval systems. Relevance feedback techniques were incorporated into CBIR to produce more precise results by taking user's feedbacks into account. Existing relevance feedback-based CBIR techniques, however, typically require a number of iterative feedback to produce refined search results, throughout an database of images. In actual implementations, this is impracticable and wasteful. SPARQL, a query language that gathers data from various sources and accelerates Web 2.0 application creation, provides a standard web service for anything that asks a question.The fact that "Query optimization" defines some of the rules for rewriting query which transform execution structure of query. 'Query Execution' is the step in which the SPARQL query is evaluated by the query engine by generating the QEPP (Query Execution Plan). SPARQL has been used to derive user perception information that can be tailored for potential image techniques.
Large data exploration and retrieval using domain ontology and semantic

II. COMPLEXITY IN IMAGE RETRIEVAL

For image retrieval and comprehension, image annotation plays an important role. For the assignment of keywords to pictures, various techniques have been proposed. Searching for annotated images with identical visual features is one of the most widely used methods. and keywords are transferred to new coming images. Major problem in the use of keywords is the complexity between words and concepts due to synonymy (different words denote the same concept) or homonymy (same word denotes different concepts) and many search criteria cannot be well described by a few keywords [13]. Current researches [14] conclude that key word based searching cannot be successful alone. The quality of the image and the nature of the image play an important role in finding a target image.

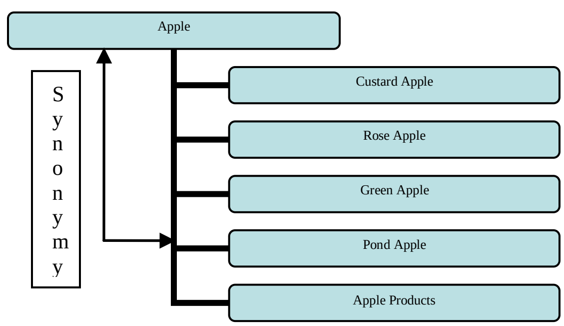

Fig 1: Example of synonymy vs. homonymy

2.1. Overview of Image Retrieval

An image retrieval system is a computer system designed to browse, scan and retrieve images from a large digital image database.. Several criteria can be considered in order to classify image retrieval systems:

i) User interaction, typing text or inserting a image that is visually similar to the target image.

ii) Search performance, how the search engine actually searches. For instance, the search can be accomplished through the analysis of visual features or through semantic annotations.

iii) Domain of the search, standalone search engine, only executes a search in a local computer versus internet based search engine.

This analysis is focused on two major paradigms which are content-based image retrieval and semantic-based image retrieval. Depending on the quality of the metadata, the latter is split into two groups: text-based image retrieval of metadata and ontology-based image recovery. In the application of remote

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sensing information, ontology-based semantic retrieval can overcome the complexities. By using semantic queries in archives, it can be further improved by mining the interrelationships between domain concepts and their properties to satisfy the requirements of users [3].

III. CONTENT BASED IMAGE RETRIEVAL

CBIR or content-based image retrieval is the application of computer vision to the image retrieval problem. Recently, several CBIR systems, including QBIC, MARS, PicHunter, and others have been developed. In a typical CBIR method, for image definition and indexing purposes, low-level visual image features (e.g., colour, texture and shape) are automatically extracted. To search for desirable images, a user presents an image as an example of similarity. The system then returns a set of similar images based on the extracted features. These systems employ image processing technologies to extract visual features and then apply similarity measurements to them. Image annotation refers to the recording of information on an image to give it a special identity. In order to represent and index image material, low-level visual characteristics such as colour, texture, and shapes can be easily extracted from images [13]. However, they are not completely descriptive for meaningful retrieval. In retrieval, high-level semantic knowledge is useful and effective. But it is highly reliant on semantic regions that are difficult to obtain. An unresolved "semantic gap exists between low-level features and high-level semantic information. Two inherent issues account for the semantic difference. One issue is that it is incredibly difficult to derive full semantics from image data as it requires general object recognition and comprehension of the scene. Other related complementary disciplines such as knowledge-based systems, computer vision, data processing, neural networks and so on should also be integrated into the CBIR system[15].Despite encouraging recent progress in object detection and recognition, unconstrained broad image domain still remains a challenge for computer vision. The system is evaluated based on a new effectiveness measure in addition to the common precision/recall measures[16]. The calculation of effectiveness has four parameters: the number of relevant images in the database (R), the number of images returned (E), the number of relevant images returned (Rr) and the number of relevant images missing (Rm = R-Rr) where the specifics of the formula are referenced.

3.1 Types of Image Search

The increasing demands of handling the large number of current multimedia documents, such as hyper-spectral remote sensing images, have rich spectral characteristics and are very important for small samples of remote sensing images, selection of features, mining of features and integration of features. For multiple tasks such as feature selection, function mining, and feature integration during training, a single model is difficult to implement.To improve the classification of small samples, a sequential joint deep learning algorithm[4] with Query by-Example (or QBE) can be used in many remote sensing images for ranking the elements in a database according to their similarity to a “query image” [5,6].Since a user’s concept of similarity is largely semantic, the efficiency of the search process in QBE affected by the “semantic gap”—the discrepancy between the low-level representations of images and the high-level descriptions meaningful to users [7, 8]. Indeed, in many cases, images that present similar low level descriptors may have very different semantic content. A partial solution is provided by relevance feedback (or RF): divide the search session into several rounds and solicit information from the user at each step, for example by asking the user to declare which displayed images are “relevant” and which are “irrelevant” with respect to the desired target category. GA allowed ontology for the free dynamic semantic web platform to enhance the metadata quality of the web to make it more meaningful. Similarly to Bootstrapping Ontology, the analysis of the extracted token is performed using TF/IDF for word ranking, Genetic Algorithm to find the promising area to classify appropriate words and fuzzy logic for ontology mapping[9,10].

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A. *Category (subject) search:* To retrieve an arbitrary image that represents a specific class, similar images are cluster and navigation through a domain hierarchy allows getting to the target subject and then browsing or searching only that limited subset of images.

B. *Search by image:* Having no specific aim and iteratively refined on the basis of the user's relevance feedback. Search for a specific image or Query-by-X where "X" can be *Image example* or a group of examples (Query-by-Example, or QBE) specified by a user virtually anywhere in the Internet; in the descending order of the similarity ranking, the images that are most similar to the query image(s) are shown.

To improve the metadata quality of the web to make it more relevant, GA allowed ontology for the free dynamic semantic web platform. Similar to Bootstrapping Ontology, using TF/IDF for word ranking, Genetic Algorithm to find the promising area for classifying acceptable terms and fuzzy logic for ontology mapping, the study of the extracted token is carried out[9,10].

IV. RELEVANCE FEEDBACK MECHANISM

Typically, relevance is characterized by a feature that certain images share. It can be a perceptual characteristic or a more semantic one, and it may concern entire images or parts of images. General assumptions to be consider when invoking RF mechanisms for CBIR:

1. The discrimination between "relevant" and "irrelevant" images with the image descriptors available must be possible.
2. The topology of the definition space has a reasonably clear relationship with the characteristics shared by the images that the consumer is looking for.
3. "Relevant" photos are a tiny part of the whole collection of images.
4. While part of the early RF work presumed that the user could (and will be able to provide a very rich input for many images, including "relevance notes," the current expectation is that this feedback information is scarce: only a few "relevant images would be marked as positive and some rather distinct images as negative by the user[17].

Image retrieval is a dynamic method that inherits techniques such as pattern matching, information retrieval and computer graphics from various fields.

V. CLUSTERING TECHNIQUE FOR IMAGES

The word “Apple” is used to annotate target image but there is complexity between word and its concept, its meaning varies depending upon the domain. Image databases based on textual annotation has major drawback that the annotations and textual descriptions, are often ambiguous [15],[16]. Google recently offers a way to search for images based on textual information found in the context of images. For example, the search for “Apple” images results with custard apple, rose apple, green apple, and pond apple and apple products. Customizing images of large database is complex task; the problem can be overcome to some extent by using clustering technique. Both Hierarchical and K-Means clustering technique can be used for categorizing image clusters. In order to improve the efficiency of image retrieval system a hybrid clustering technique by incorporating the eminent features to two clustering namely hierarchical and K-Means clustering can be used.
To improve the recovery speed, the Hierarchical Algorithm is used to group related images into clusters.

K-Means is an iterative refinement of heuristic algorithm that works faster compared to hybrid clustering technique. A popular approach is to run the algorithm to regain the best clustering.Agglomerativehierarchical clustering is a bottom-up clustering method can be used to cluster the search results into different semantic categories.

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VI. SEMANTIC IMAGE ANNOTATION AND RETRIEVAL

Early contribution to image retrieval were focused mainly on reliable extraction of specific semantics, e.g Differentiating indoor from outdoor scenes, towns from landscapes, among others and distinguishing trees, horses, or houses. As one of supervised learning, these attempts raised the problem of semantic extraction: a collection of training images with and without the concept of interest were gathered and a binary classifier trained to detect the concept of interest. Generically speaking, unsupervised labelling leads to substantially more flexible training procedures (in database size and number of concepts of interest), putting much lower demands on the quality of the manual annotations needed for bootstrap learning, and creating a natural ranking of keywords for each new image to be annotated[17][18]. On the other hand, it does not specifically consider semantics as image classes and thus offers no assurance that in a recognition or retrieval context, semantic annotations are optimal[19]. Semantic image annotation that manages all the available image data at the same time (contextual, spatial, and spectral). We use remote sensing ontology as a semantic resource and create an annotation method that helps enhance image understanding and retrieval by creating a graph describing objects of a scene as well as their spatial relationships[12].

VII. ONTOLOGY SUPPORT FOR IMAGE ANNOTATION

The concept of ontology is fundamental to the semantic web. Considering a domain (e.g. science, sports, geospatial, etc.), “its ontology forms the heart of any system of knowledge representation” for that domain. Without ontology, or the conceptualizations that underlie knowledge, there cannot be a common vocabulary for representing and sharing knowledge. Ontologies provide computer-usable descriptions of and relationships between basic concepts in the domain. [14]. The Ontology Web Language (OWL) [18] has become the de-facto standard for expressing ontology. It adds extensive vocabulary to describe properties and classes and express relations between them (such as disjointness), cardinality (for example, "exactly one"), equality, richer typing of properties, and characteristics of properties (such as symmetry). Image Ontology is constructed using Class, Properties and instances. The Protégé software is used in creating classes, properties, Instances and mapping the images to its respective classes. The RDF/XML codes are automatically generated which represents RDF graph. The low level features of an image are represented in separate class. This metadata provides the general concepts of an image. The high-level definitions of external data source image descriptions are gathered and encapsulated into groups and instances. Assertion types are integrated into the respective class of the associated image.

7.1. Ontology Development

Ontology to represent three domains for image search: Locations, Subject, and Theme. It is chosen on the basis that general photographs will have a location associated with it, have a subject in the photograph (e.g., an animal, person). Person will often have some theme attached such as emotion or behavior. Combined, they comprise the “Image Search Ontology" used in the keyword generation system and involve over one thousand instances over two thousand relationships.

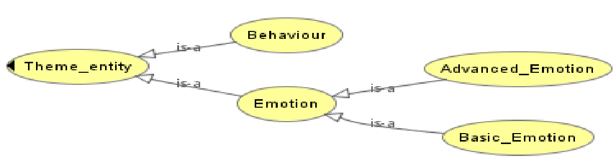

Fig. 2. The Theme Ontology

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Semantic Web languages are designed explicitly for representing ontology RDF Schema. A key format for semantic web data representation is the Resource Definition Structure (RDF). RDF is a structure for the representation of resource knowledge in a graph type. It was mainly designed to represent WWW resource metadata. With the Web Ontology Language OWL, Ontology can be developed. The OWL is a language derived from the logic of description and provides more RDFS constructs[23]. It is integrated syntactically into RDF, so it offers additional structured vocabulary, including RDFS. OWL comes in three kinds: OWL Lite for taxonomies and basic constraints, OWL DL for logic support for complete definition, and OWL Full for RDF's maximum speech and syntactic freedom[39]. Recent advances in the field of Image Information Mining(IIM) are aimed at bridging the gap between image characteristics of the low level and semantics of the higher level. This study focuses on enhancing the semantic interpretation from a spatio-contextual perspective of a remote sensing scene during the flood disaster. It is important to understand the flood inundation and receding patterns in relation to the spatial arrangements of land use/land cover in the flooded area during a flood event In relation to the flood disaster phenomenon, Flood Scene Ontology (FSO) can be used to derive topological and directional information. Ontology-based image annotation for (contextual, spatial, and spectral) image retrieval would be an important method in the future[40]..

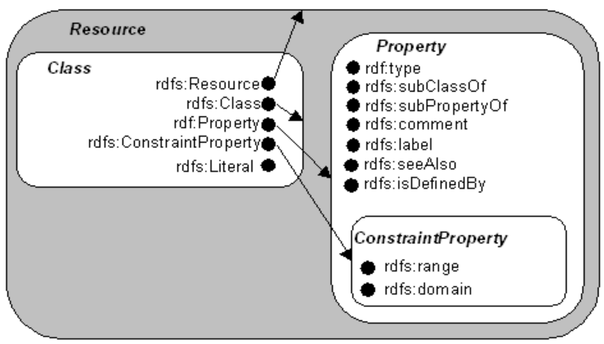

Fig 3: RDF Schema Specification

7.2. Ontology Based Image Retrieval

Ontology refers to a formal representation of a set of concepts within a domain and the relationships between those domains, and semantic annotation is to describe the semantic content in images and retrieval queries. *M*ajor image retrieval paradigms are text based and content based. In practical applications both have limitations. Ontology-based image retrieval has the ability to completely explain the image's semantic content, enabling accurate computation of the similarity between images and the retrieval query[20]. Semantic technologies like ontology and the OWL language provide tools for a promising new approach to image retrieval based on implementing semantic understanding of image content. Ontology-based image retrieval has two components: semantic image annotation (focuses mainly on the description of image content) and semantic image retrieval (to allow searching and retrieval based on image content) [20][21]. These two principles are essentially used by an ontology based image retrieval system: ontology and semantic annotation. In addition, the semantic annotation of an image or retrieval query still involves the involvement of a human being who is an open field of study, making it automated and interactive similar to some of the CBIR systems based on a combined visual feature[22].

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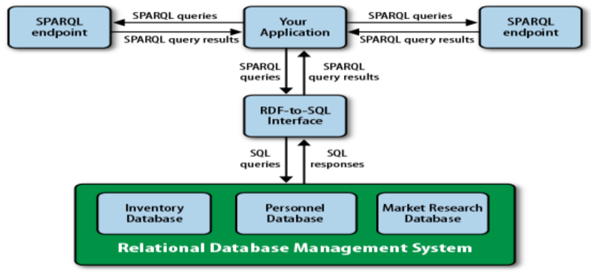

Fig 4: A framework to access database using SPARQL Queries

In the current knowledge management and artificial intelligence literature, the construction of domain ontology from scratch has been carried out by many different approaches to the issue[24]. All of these methods deal fundamentally with three problems: (1) providing a set of general terms defining the classes and relationships to be used in the domain itself description; (2) organizing the terms by the ISA relationship into taxonomy of the classes; and (3) expressing specifically the constraints that make meaningful the ISA pairs[25]. Although it is possible to find a variety of such approaches, there is no systematic study of them that can be used to understand the motivating inspiration, sense of applicability, and method structure[26][27].

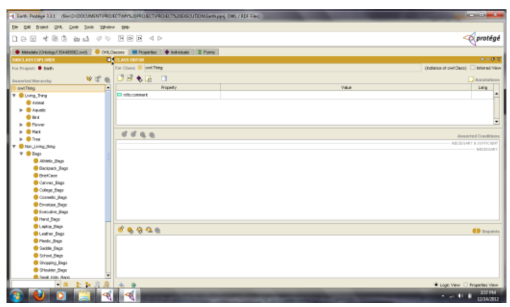

Fig 6: Earth Ontology.

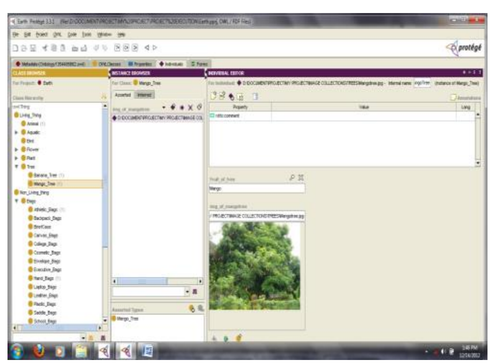

Fig 6: Ontology based image retrieval of mango Tree.

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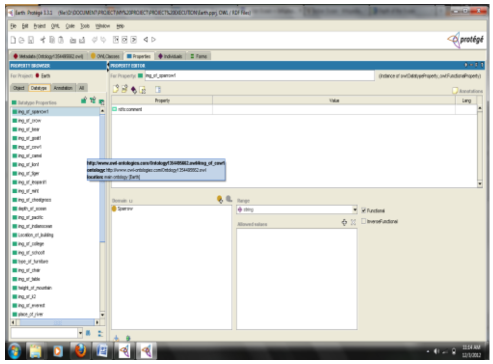

Fig 7: Illustration of Properties for Earth Ontology.

Fig 5 shows the Earth ontology which is developed using OWL Classes such as Living thing and Non Living thing. The classes are subdivided as subclass of living thing such as flower, animal, bird, plant, tree where as subclass of non living thing are mountain, river, bags, building, furniture, sea. Fig 6 shows the annotation of mango tree from the subclass of tree. The mango tree can be classified based on the cultivation, name of mangoes and nutrients. Fig 7 shows the properties of the Earth ontology. We provide a structure for the study of the current methodologies in this paper that compares them to a collection of general criteria. In particular, we obtain a classification based on the direction of ontology construction; bottom-up are those methodologies that begin with some domain descriptions and obtain a classification, while top-down methodologies begin with an a priori given abstract view of the domain itself. The resulting classification is useful not only for theoretical purposes, but also for the practice of ontology implementation in information systems. since it provides a framework for choosing the right methodology to be applied in the specific context, depending on the needs of the application itself [28].

VIII. SPARQL

SPARQL works with the W3C's Resource Description Framework (RDF) for representing data and the Web Services Description Language (WSDL). Traditional query languages such as SQL are designed for accesses to a single source of data, and have not performed well when the results from several sources need to be merged. SPARQL can create a single query for multiple sources and combine the results [29]. SPARQL, a query language designed to gather data from multiple sources and speed the development of Web 2.0 applications, creating a standard web service for anything that asks a question[30]. SPARQL Icon Ontology is used for a collection item without its own custom image, which is controlled through the icon ontology defined by schema graph , icon instance data in graph and rules in graph Together, the icon schema graph and instance data define various generic display classes: vpi:Thing, vpi:Person, vpi:Place, vpi:Book, vpi:Music etc and associate an icon with each, e.g. vpi:ThingIcon, vpi:PersonIcon etc. The default icon set generated by describe? S from where {?s ?p ?o } is shown below[35][36].

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Fig 8: SPARQL Icon Ontology Results

The collection of view classes that are predefined includes Event, ImageGallery, MailMessage, MessageBoard, Music, Individual, Location, SkiResort, SubscriptionList, Survey Set, Thing, TouristDestination, VCard, Weblog, and Wiki. AddressBook, BeachResort, Book, BookmarkFolder, Briefcase, Company, Calendar, Community, ElectronicGood, The semantic ontology model together with image instance data can be used in finding annotations and relation with query image and other images in the repository[31][32]. There are many tools and APIs that already provide functionality for SPARQL, and most of them are up-to-date with the new requirements[33][34]. Includes a short list:

- ARQ, a Jena SPARQL processor
- Rasqal, the RDF query library included in the robust Redland system by Dave Beckett
- RDF::Query Request
- Twinql, a SPARQL processor written by Richard Newman for Lisp
- Pellet, Java's open source OWL DL reasoner, which has partial SPARQL query support
- KAON2, another reasoner for OWL DL with partial SPARQL support.

My SPARQL query tool Twinkle provides the ARQ library with a simple GUI interface and supports multiple output formats and simple query loading, editing and saving facilities[37][38].

IX. CONCLUSION

Use of safe software to create ontologies to provide semantic meanings of image content.Semantic web data can be queried by using SPARQL. In CBIR systems images are retrieved using only keyword name of the concept or object. Ontology offers a unified technique to bridge human experience with image explanations of low-level visual features. Ontology Web Language (OWL) is used in the construction of ontology. Ontology can be constructed in two ways: general and domain-specific. Ontology can be used in various applications such geospatial imaging, military, medial image retrieval. User will access images from various perspectives at the higher conceptual level, the domain specific ontology stored in knowledge base is constructed to depict the domain concepts and their relationships. Ontology depicts a shared and common understanding of a domain that can be communicated across people and application systems. Ontology incorporated with SPARQL will facilitate image annotation and increase the efficiency and accuracy of image retrieval.

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