Textual Ontology and Visual Features Based Search for a Paleontology Digital Library

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***Abstract*— The *Treatise on Invertebrate Paleontology* is the most reliable information source of invertebrate paleontology research. Based on this *Treatise*, an Invertebrate Paleontology Knowledgebase (IPKB) has been built as a digital library to provide these data through a web interface. However, the search functions provided by the old IPKB system are only based on textual information, while some more important information, such as textual ontology and fossil images, are not considered at all. In order to overcome this limitation, and provide more reliable and flexible search options, we develop a new hybrid search function for the current IPKB system. In particular, we propose an approach to extract textual ontology information for each genus, as well as build a fossil image dataset where each image is tagged with its genus name. Based on the data from both sources, a hybrid search system is developed by integrating both textual and visual features, and thus, more search options are available to users and the searching results are significantly improved.**

Keywords—Information retrieval, Invertebrate Paleontology Knowledgebase, hybrid search, textual ontology

I. Introduction

Invertebrate Paleontology Knowledgebase (IPKB) [1] is a digital library version created for the *Treatise on the Invertebrate Paleontology*, which is the most authoritative compilation of paleontology data that is considered as the base source of information for all the research in this field. Previous research towards this effort [1] implemented an information retrieval system, which provides the user with a textual keywords search mechanism. Although [1] provided a base for transforming the PDF versions of the Treatise to a structured form, providing various user-friendly options that are not possible through browsing the PDF files, this is still an open research topic, giving rise to lots of challenges to enhance the intelligence of the search system. This work is an endeavor towards solving the problem. We develop a more intelligent knowledge discovery framework, which is capable of extracting Treatise information based on the fossil images and other structural information.

Previous work on the old IPKB system is purely based on unstructured text information, which cannot satisfy user requirements in many situations. Consider a scenario, where a paleontology researcher wants to query for "*small shell, round circular ventral area*". The existing system matches the user's queries against all the fossil records in the database and returns fossils that have the terms in the user query with high frequency but not as per the properties mentioned by the user. For instance, a fossil record having a description as "*large round circular shell, small ventral area*" is a perfect match for the user query as it contains all the terms in the user query. Obviously, this behavior is completely opposite to the user's intention. Moreover, sometimes it is hard to give out exact and correct query descriptions by words. The terminology used in the paleontology is highly complicated and even experts in this field face the problem of correctly spelling the terms. As a result, using images is a good option in addition to the text-based search mechanism. The paper targets at overcoming these limitations and developing a retrieval system by integrating both textual ontology and image-based information.

Content-based image retrieval (CBIR) has been extensively studied recent years. Classical approaches for CBIR make use of image features such as SIFT [12], GIST [16] and HOG [8]. Although those approaches are proved to be efficient for object detection, they do not work well for the IPKB image database since most of the images in the database are similar to each other with very limited structural and visual differences. The approaches proposed in [15] adopted statistical models to automatically annotate the images, these approaches, however, can only be applied to highly distinctive objects where the images are visually different from each other. In an early study [13], we proposed a novel approach to extracting information using the combination of textual and visual features. This approach uses the domain knowledge in order to relate the textual terms to visual features. In the work [2,3,4], natural language processing techniques was adopted to identify semantically related terms in a corpus and to tag the sentences according to their parts of speech. In addition to some classical image features, such as SIFT and HOG, other work [5,7] in the field adopted sketch-based techniques for image retrieval. Features from a single view may not represent the sample very well, some studies [13, 14] are focused on fusing or integrating features from different views.

In order to improve the performance of the IPKB system, we conducted extensive research based on our previous work [1], including extracting textual ontology, building fossil image database, and developing a new search engine. The major contributions of this paper are as follows.

- We propose a new approach to extract textual ontology information from the fossil structural descriptions, and compute the similarity between these textual ontologies;
- We construct a fossil image database and associate each

This work is partly supported by the US National Science Foundation under CDI-1028098, NSF CNS-1422206 and NSF IIS-1513324.

image with its genera name. Based on this database, we propose a modified RST-SHELO [5] descriptors to compare the similarity between different fossil images;

- We implement a hybrid search function by integrating both textual ontology information and fossil images. The new search engine allows users to select structural details of fossils and upload a set of images to retrieve the matching fossil genera.

II. System Overview

A. Background of the IPKB System

Invertebrate Paleontology Knowledge Base (IPKB) is an effort towards digitizing the vast content of the *Treatise of the Invertebrate Paleontology* [1]. At a higher level, this is a web-based search engine, which allows users to search for content based on keywords, for example, search based on the fossil names and category names, search based on other fossil information. Although these features suffice the basic features required for information retrieval, there is lot more scope to enhance the intelligence of the system, by using more advanced computational methods. The focus of this work is to add to the original IPKB more intelligent features, such as textual ontology-based information retrieval, image similarity based search, and text-image based search.

B. Overview of the Hybrid Information Retrieval System

Fig. 1. shows the overview of the proposed hybrid search engine for the IPKB system. Three major components are outlined using different colors. Note that the PTFIDF database and iRST-SHELO database are generated offline. Some results such as ontology matching and image distance score set are used by multiple components.

Textual ontology-based search provides the user with a feature of providing a region name in the shell as well as the structural properties of that region. The matching results are extracted based on the shells that have the regions with properties closer to the user's query. Thus, this feature is a text-based search using the domain knowledge of paleontology. We first identified that the description of each fossil record explains how each region and sub-region look like in a shell. This information is the major distinguishing factor between two different shells and no two shells have all the regions with identical properties. This forms the base for the novel textual ontology search in this research. Below are the major steps involved in the approach, and the details of each step will be explained in the following sections.

- Tagging the description with Parts of Speech.
- Extraction of region names using a statistical approach.
- Generate fossil ontology.
- Calculate similarity.

In image-based search, users are provide at least one query image. Images can be photos with a light background or hand drawn sketches. Image-based search consists of four major steps: image preprocessing, visual feature extraction, dimensionality reduction, and group comparison.

By integrating both the text and the image information, we propose hybrid text and image based search engine. Two types of features, PTFIDF and iRST-SHELO, are designed and generated in order to gain information from both textual ontology information and images. As demonstrated by the experiments, the search results from the textual ontology are greatly improved by introducing the image information.

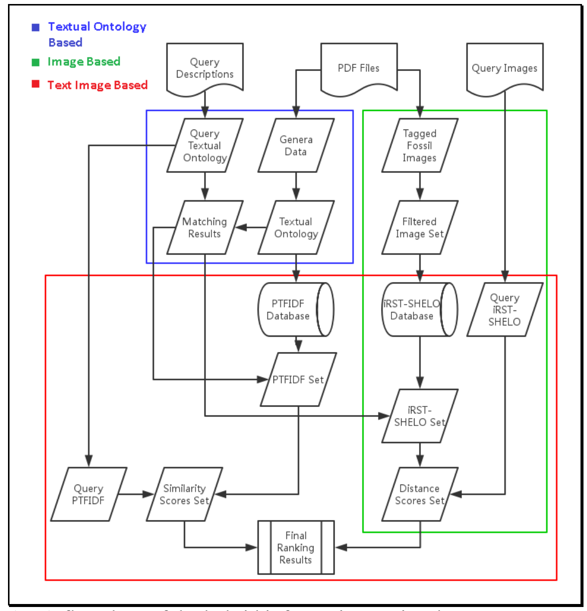


Fig. 1. A flowchart of the hybrid information retrieval system.

III. Textual Ontology-Based Search

In [1], we have generated a textual description of each genus in Part H of the Treatise, which is the data source of our textual ontology-based search. In this section, we will discuss our method for extracting ontology data and computing similarities among genera based on the data.

A. NLP PoS Tagging

The first step of ontology construction is to identify region names from the descriptions of the genera. We identify the non-independent terms from our dictionary following the idea in [2]. We tag the sentences with the appropriate POS (parts of speech) tagging. POS tagging is one of the major steps in the construction of fossil ontology. We use Stanford NLP tagger API [3] in this step. This API tags non-dictionary words with an approximation. Hence, this tagger is useful with the paleontology data that have a lot of scientific terms. A sample POS tagging for the sentences extracted from IPKB is shown in Table I. below.

TABLE I. Sample POS Tagged Sentences

Sentence	POS Tagged
Shell elongate oval to subrectangular	shell/NNP elongate/JJ oval/JJ to/TO subrectangular/JJ
vascular media absent	Vascular/NNP media/NN absent/JJ
Transmedia scars possibly asymmetrical	transmedia/JS scars/NNP possibly/RB asymmetrical/JJ

B. Automatic extraction of non-independent terms

Non-independent words are semantically related to each other and they carry important semantic information. A hypothetical testing method is used to identify such terms across the corpus and the information will be used in the construction of ontology to capture all fossil description. Statistically, two terms *w* and *w`* are non-independent if by chance they co-occur in a sentence more often than expected.

U-test: Let *n* be the number of sentences (separated by a semicolon or period) in the corpus, (*w, w`*) are pair terms from the corpus, *c* (*w), c* (*w`*), and *c* (*w, w`*) denote number of sentences with the terms *w, w`*, and both *w, w`* respectively. P (*w, w`*) is the co-occurrence probability of the terms *w, w`*. The null hypothesis, $H_0$ assumes that *w* is independent of *w`* and thus the co-occurrence frequency of (*w, w`*) could be approximated by p = *c* (*w*) *c* (*w`*) / n^2. The *u*-score of two terms can be calculated as:

$$|u| = \left| \frac{n\,c(w, w^{`}) - c(w)c(w^{`})}{\sqrt{n\,c(w)c(w^{`})}} \right| > u_{\alpha/2} \qquad (1)$$

Given a significance level α, if the *u*-value of two terms $|u| > u_{\alpha/2}$, then H_0, is rejected, i.e. *w* and *w`* are non-independent, otherwise, they are not related to each other.

Algorithm: We have extracted the descriptions of all the fossils from volume H of the Treatise. As we are dealing with textual ontology, the formatting and way of narration of the words are of high importance and as each volume has a different style of narration, we restrict our current research to volume-H to keep things in synch. A total of 4,427 fossil descriptions are extracted and are split into sentences using semi-colon and period symbols as delimiters. Each sentence of a fossil description explains about the structural properties of a region (or sub-region) of that fossil. We have a total of 29,051 sentences in our corpus. The algorithm to extract semantically related terms is given below.

- Split all the descriptions into sentences using semicolon and period as delimiters.
- Tag each word in the sentences with an appropriate POS tag using the Stanford NLP POS tagger.
- In order to calculate the *u*-score of each pair of terms, extract all pairs of adjacent Noun + Noun and Adjective + Noun and collect their frequency information as explained above (*c*(*w*) , *c*(*w`*) and *c*(*w, w`*)).
- Using the frequency information, we calculate the *u*-score for each pair of terms as shown in equation (1).
- Sort the terms in decreasing order of their *u*-scores and identify the pairs that have *u*-score greater than $u_{\alpha/2}$ = 2.575 (At significance level α = 0.01, α/2 –Quantile of standard normal distribution is 2.575) as the compound terms or region names.

The bove algorithm is executed separately for the N + N pairs and Adj + N pairs and the identified compound terms are combined in the corpus and tagged with a new tagging shortcut (NNP_GLO), to be useful in the next step (ontology construction). A total of 471 compound terms were extracted and then updated in the corpus as NNP_GLO terms.

C. Fossil Ontology Generation:

We have identified all the region names from the IPKB system and tagged them with new tag names: NNP_GLO. A few observations can be drawn based on the tagged fossil sentences, a) each sentence in the genera description explains about either the whole shell or dorsal view or ventral view. b) Each of these views explains the certain region and sub-region in that view. c) The properties of the regions and sub-regions can be pure adjectives (rectangular, stretched) or related to another region in the shell. d) If we can extract the properties of the major regions as identified, that could be sufficient to generate an ontology that distinguishes different genera. e) Based on the organization of the sentences and using the semantic relationship between POS tags, a few rules were identified and ontologies are extracted based on those rules. The rules to construct fossil ontology are as follows.

- Each sentence will begin with the term: shell or ventral or dorsal. This is the first level property of the region.
- The conjunctions "*with*" and "*and*" specifies about two different regions or sub-regions within a region in the same sentence. So sentences can be separated.
- All the regions or sub-regions that appear in the sentence starting with either shell or ventral or dorsal explains the properties of that subregion in that view.
- All the adjectives (JJ or JS) that occur prior to the region names are the descriptors for the regions and should be considered as the part of the region.
- All the words till the end of a sentence that follow region names are the properties of that region in that view.

Using the above rules, all the 29,051 sentences are parsed and the textual ontologies are generated for all the 4,427 fossils. Each fossil's ontology explains most prominent regions in that fossil and gives a set of terms that structurally explains that region. For the tagged sentences of a fossil "*Lingula"* from the Treatise, the extracted ontology based on the above rules is shown in Fig. 2.

```
Lingula:
    shell :elongate oval to subrectangular
    ventral pedicle_groove :wide triangular
    ventral visceral_area :extending to midvalve
    ventral impression of pedicle_nerve :curving around unpaired umbonal muscle_scar
    dorsal visceral_area :extending somewhat anterior to midvalve
    dorsal central muscle_scars :and closely spaced , bisected by weak median_septum
    dorsal anterior lateral muscle_scars :and closely spaced , bisected by weak median_septum
    dorsal vascula_media :absent
```

Fig. 2. Textual Ontology for genus Lingula.

D. Algorithm for calculating similarity score

As the textual descriptions explain how a region looks like inside a shell, region wise similarity between two genera should explain how similar they are textually. Ontology extracted will give the exact details of region names and their properties. Calculating the textual similarity between ontologies of two genera should give a score that describes how close they look textually. The algorithm to estimate the similarity score is given below.

- Four different scores are calculated for each pair of genera: shell score, ventral view score, dorsal view score, and cumulative score from other regions.
- All the scores have equal weights: Each of them is scaled down to a value between 0 and 1.

- Shell score is a single score based on the textual similarity between shell properties of two fossils.
- Ventral and dorsal scores: Sum of the similarity scores of the sub-regions in ventral and dorsal views divided by a total number of matching regions. (0-1).
- Other regions score: Sum of the all other regions (apart from the shell, dorsal, and ventral regions) similarity scores divided by a number of other regions.

All the 4 scores are then divided by 4 to normalize the overall score between 0 and 1. The rules used for assigning scores based on different levels of semantic similarity between two sentences is as explained below. The similarity is calculated between the matching regions in both fossil ontologies. Each matching key-value will generate a score.

- If two properties are totally identical (exactly the same). Then the score is 1.
- Else: each property, in turn, can have multiple sub-properties separated by commas if there are matching sub-properties in two fossils, then score = (number of matching properties divided by total number of properties)
- Else: word based similarity is calculated if there are no properties matching, as score = number of matching words divided by total number of words.
- Else: there are no common terms between the two fossil properties, which means they are semantically not related, and hence, the score is assigned as 0.

The score calculated this way is summed up separately for the properties that belong to different views and then divided by the number of regions in that view and are summed up to determine the final score.

IV. Image Based Search

Our goal here is to find images that are visually similar to query images, rather than identifying the genera names of the queries. In this section, we present techniques for image-based search. Image dataset and visual features generated in this part are also used in text-image based search.

A. Image Data Set Preprocessing

Image-based search is solely based on images of fossils in the image database. In our previous work, we have already built an image set containing more than 30,000 images, each of which is tagged with its genus name. In this dataset, not all images can be used for visual feature extraction. Some of them are too small or just hand-sketched which could not represent meaningful shell, dorsal, or ventral information of a fossil. Therefore, before the feature extraction step, we designed a method to separate usable images from others.

We first chop each image to keep the fossil object in the center and leave only narrow white margins around it. The image set can be divided into two groups using (2):

$$im \in \begin{cases} G_1 & if \ \ t < M/C, \\ G_2 & otherwise \ . \end{cases} \tag{2}$$

where M is the number of white pixels, C is the number of all pixels in the image, and t is a threshold value. After parameter tuning, we are able to put 90% images into the group G_1, which is selected as our final image set.

B. Visual Feature Extraction

Since the image dataset only contains grayscale images, we do not consider color issues. Instead, shape, contour, and texture are three important properties we need to take into account. In order to meet all these assumptions, we adopt RST-SHELO [5] approaches to extract visual descriptors.

RST-SHELO includes three important steps. The first step is pre-processing for both query images and training images. After contour detection using canny algorithm [6], sketches of images are generated by a cropping operation followed by a dilation operation. The second step is RST-SHELO descriptor generation. This step is a combination of SHELO [7] descriptor generation and a square root normalization [5]. Just as HOG [8] features, SHELO features are actually gradient-based. Inspired by the idea of HOG and HELO, both of which are visual features in SBIR area, in square root normalization, the idea of Hellinger kernel [9] is adopted for SHELO [7] features as normalization before the last step. The third step is similarity search based on the Euclidean distances.

C. Dimensionality Reduction and Group Comparison

In order to keep both correctness and efficiency of group comparisons in next stage, we use principal component analysis (PCA) [10] to reduce their dimension. By setting the threshold to 80%, the size of the dimension is reduced from 1,296 to 206. We call the final descriptors we generated iRST-SHELO. Since most genera contain no less than 3 images and there could be multiple query images, we use group comparisons in our application.

Fossil images within each genus may vary a lot due to the angles of photos taken. If one of the query images looks pretty similar to one fossil image in a genera set, then this genera set (group) should be ranked higher. In this way, we use a modified version of Heuristic Measure[11] for our group distance calculation. The distance between two groups in our image set is calculated using

$$\begin{aligned} &Dist\,(G_1, G_2) = \min(\,dist\,(I_{1i}, I_{2j})), \\ &(I_{1i}, I_{2j}) \in (G_1 \times G_2). \end{aligned} \tag{3}$$

where *G1* and *G2* stand for different groups, and *I* stands for images inside these two groups. The distance between two images is calculated using the Euclidean distance based on iRST-SHELO descriptors.

V. Text-Image Based Search

The basic idea of the text-image based search strategy is as below: First, we use text searching method to obtain relevant results. The number of relevant ones is much smaller than the total number of genera, which helps speeding up our future calculation. Then, we execute combined searching for these relevant results. Visual (iRST-SHELO) features and a newly designed parallel TFIDF features (PTFIDF) features are fused together to determine the final ranking scores for each genus.

A. Parallel TFIDF

In the pure-text searching process, similarity scores are generated, however, we still need a feature representation for each genus. PTFIDF features achieve this purpose by taking four types of TFIDF weights (shell, ventral, dorsal and others). The TFIDF weights for each type are calculated respectively with its corresponding descriptions. Thus for each genus, we have four PTFIDF feature vectors.

B. *Combination of Text and Visual Features*

Based on the PTFIDF and the iRST-SHELO generated above, we re-rank the search results by using both text and image information at the same time. In the following, we describe our algorithm for fusing PTFIDF and iRST-SHELO features together. First, we take the centroid of four PTFIDF vectors for both the query input and the genera. Then, calculate the cosine similarity (S) between these two centroid vectors. Next, we calculate the group distance (D) between two genera's image set, and the final similarity scores for the query input and a genus in the data set is calculated as follows:

$$S' = S + \lambda \frac{1}{1+\ln(D+1)} \tag{4}$$

where λ is the parameter to balancing the weight between *S* and *D*. The final similarity scores determine the final ranking of the searching results.

VI. Experimental Results & Analysis

A. *Textual Ontology-Based Search*

In order to demonstrate that the new search approach based on textual ontology overcomes the drawbacks of the old IPKB system, we analyzed the similarity score between the fossils that belong to the same family to validate if fossils belong to similar family poses visual similarity.

Fig. 3. shows 7 different types of the genera which belong to Family "*Lingulidae*". We ran our textual ontology similarity algorithm to calculate the similarity between each of these fossils. The results of the similarity test are as shown in Table II. The results clearly show that a high similarity score is assigned to the fossils that look visually similar, whereas the score decreases as they look different. This clearly proves that the textual ontology we extracted and our similarity measurement algorithm is able to uniquely identify a fossil based on its structural properties.

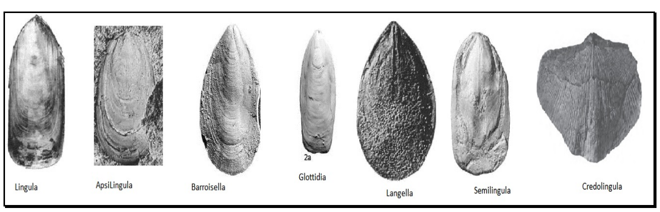


Fig. 3. Images of genera from family Lingulidae.

In order to improve the intelligence of our textual ontology search system, we added a new user interface to the existing system that enables the user to provide a set of region names and their properties. The fossil records retrieved using our new approach when compared to the existing textual keyword search has clearly shown the improvement in the relevancy of the data retrieved as explained in the previous sections.

TABLE II. Textual Ontology-Based Similarity between Fossils of Family Lingulidae.

Genera 1	Genera 2	Similarity Score
Lingula	Apsilingula	0.65
Lingula	Barroisella	0.25
Lingula	Glottida	0.13
Lingula	Langella	0.25
Lingula	Semilingula	1.0
Lingula	Credolingula	0.0
Apsilingula	Barroisella	0.5
Apsilingula	Glottida	0.06
Apsilingula	Langella	0.5
Apsilingula	Semilingula	0.53
Apsilingula	Credolingula	0.0
Barroisella	Glottida	0.0
Barroisella	Langella	1.0
Barroisella	Semilingula	0.42
Barroisella	Credolingula	0.0
Glottida	Langella	0.25
Glottida	Semilingula	0.13
Glottida	Credolingula	0.0
Langella	Semilingula	0.42
Langella	Credolingula	0.0
Semilingula	Credolingula	0.0

For query "*small and rounded to subtriangular shell*", the comparison between top result retrieved using textual search and the ontology search are shown in Fig. 4 (a) and (b), respectively. It is evident that the textual search results are mostly irrelevant as the retrieved results are just the records having the query terms, rather than those possess the properties that user queried for. Whereas the ontology-based search results are more relevant to the user query, as it matches the region names as well as the properties.

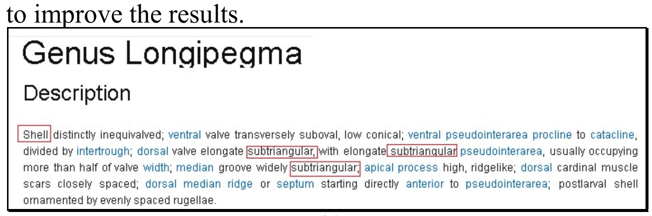
B. *Image Based Search*

We built an image data set of 18,822 fossil photos, where each image is tagged with its genus name. The iRST-SHELO feature vector is calculated off-line.

Fig. 5 shows a sample querying result using a single image. From the results, we can see that the top 9 results are very similar to the query image at the up left corner.

C. *Text-Image Based Search*

In this experiment, there are in total 3,829 items in the PTFIDF dataset, which is exactly the number of genera in the database. By making use of results of textual ontology search, we do not need to go through all entries in the PTFIDF and iRST-SHELO datasets, thus, we are able to save a lot of running time. In this experiment, we use the same query terms as in the textual ontology search experiment. In addition, we allow the user to upload images to improve the results.



(a)


Genus Amoenirhynchia

Description

Small, triangular, moderately equibiconvex, costae low, rounded, developed only anteriorly, no distinct sulcus and fold, anterior commissure rectimarginate or incipiently uniplicate; beak suberect, ridges distinct, planareas well developed.Dental plates long, subparallel to ventrally convergent, pedicle collar absent; septum low, septalium short, present only posteriorly; hinge teeth without crenulation; crura raduliform to incipiently flared.

(b)

Fig. 4. Search Results for the term "small and rounded to subtriangular shell ". (a) Textual search results; and (b) ontology search results.

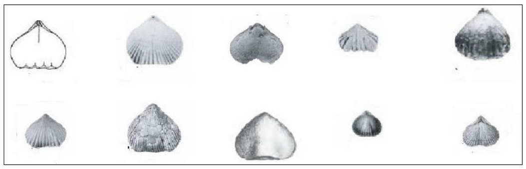


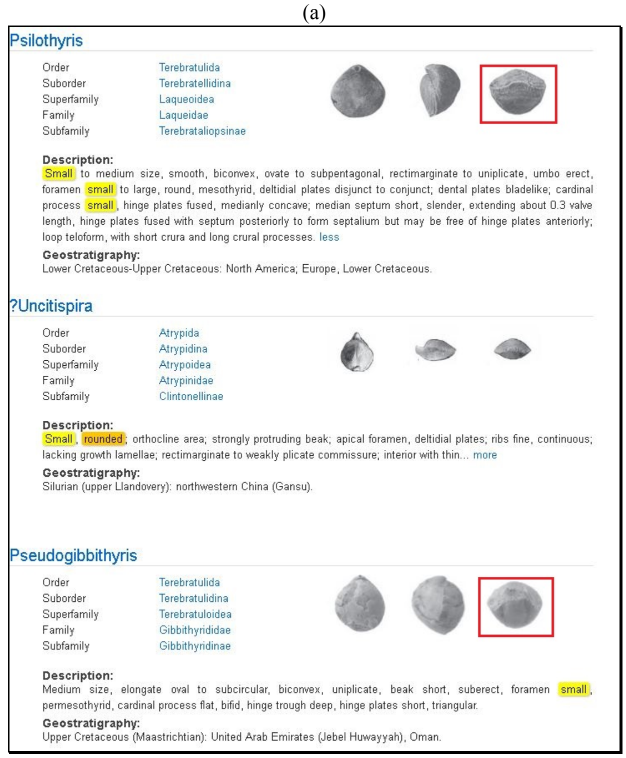
Fig. 5. Top results for iRST-SHELO, with a query image at top-left.

Fig. 6 shows the query image and final search results. We can see that, based on our approach, the top 3 results reflect the textual ontology information in their descriptions. Moreover, among the top three genera, we can see that "Psilothyris" and "Pseudogibbithyris" contain pretty similar fossil images as the query image in their image set. Compared to the results of the textual ontology-based search, in which "Psilothyris" is only ranked at the last position on the first page, we can demonstrate the advantage of using both textual ontology and image information.

VII. CONCLUSION

In this paper, we have reported our most up-to-date results in IPKB information retrieval by adding some more advanced features and functions to the existing system. In the study, we designed a new technique to extract fossil ontology descriptions, rather than directly using all terms in the genera descriptions as in pure textual search. Furthermore, in order to use information from fossil images to improve the search results, we built an image dataset, which contains more than 18,000 images tagged with their genera names and extracted iRST-SHELO features for each image in the dataset. Based on the textual ontology information and the iRST-SHELO features extracted from our proposed image dataset, we designed and implemented a novel hybrid information retrieval system by integrating both textual and visual information. Extensive experiments demonstrated the advantages and effectiveness of our new search engine over the previous one.

(a)



Psilothyris

Order	Terebratulida
Suborder	Terebratellidina
Superfamily	Laqueoidea
Family	Laqueidae
Subfamily	Terebrataliopsinae

Description:
Small to medium size, smooth, biconvex, ovate to subpentagonal, rectimarginate to uniplicate, umbo erect, foramen small to large, round, mesothyrid, deltidial plates disjunct to conjunct; dental plates bladelike; cardinal process small, hinge plates fused, medianly concave; median septum short, slender, extending about 0.3 valve length, hinge plates fused with septum posteriorly to form septalium but may be free of hinge plates anteriorly; loop teloform, with short crura and long crural processes. less

Geostratigraphy:
Lower Cretaceous-Upper Cretaceous: North America; Europe, Lower Cretaceous.

?Uncitispira

Order	Atrypida
Suborder	Atrypidina
Superfamily	Atrypoidea
Family	Atrypinidae
Subfamily	Clintonellinae

Description:
Small, rounded; orthocline area; strongly protruding beak; apical foramen, deltidial plates; ribs fine, continuous; lacking growth lamellae; rectimarginate to weakly plicate commissure; interior with thin... more

Geostratigraphy:
Silurian (upper Llandovery): northwestern China (Gansu).

Pseudogibbithyris

Order	Terebratulida
Suborder	Terebratulidina
Superfamily	Terebratuloidea
Family	Gibbithyrididae
Subfamily	Gibbithyridinae

Description:
Medium size, elongate oval to subcircular, biconvex, uniplicate, beak short, suberect, foramen small, permesothyrid, cardinal process flat, bifid, hinge trough deep, hinge plates short, triangular.

Geostratigraphy:
Upper Cretaceous (Maastrichtian): United Arab Emirates (Jebel Huwayyah), Oman.

(b)

Fig. 6. Text-image based search. (a) Query Image; and (b) top 3 results.

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