Content-based Multiresolution Indexing and Retrieval of Paleontolgy Images

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ABSTRACT

In this article a research work in the field of content-based image retrieval in large database applied to the Paleontolgy image database of the *université de Bourgogne*, Dijon, France called "TRANS'TYFIPAL" is proposed. Our indexing method is based on multiresolution decomposition of database images using wavelets. For each kind of paleontolgy images we try to find a characteristic image representing it. This model image is computed using a classification algorithm on the space of parameters extracted from the wavelet transform of each image. Then a search tree is built to offer users a graphic interface for retrieving images. So that users have to navigate through this tree to find an image similar that of to their request. Our contribution in the field is the building of the model and of the search tree to make user access easier and faster. This paper ends with a conclusion on first coming results and a description of future work to be done to enhance our indexing and retrieval method.

Keywords: Content-based Image Retrieval, Multiresolution Analysis, Wavelets, Paleontolgy Images Databases, TRANS'TYFIPAL

1. INTRODUCTION

Due to the exponential growth of the Internet, a lot of multimedia databases became available online proposing texts, images, videos and sounds to web surfers. The problem of retrieving information into these large bases quickly appeared. How to quickly find a specific multimedia resource from a large database ? In our work, we try to answer this question for still images only from a single image database (it is already a large problem).

The first methods used were based on keywords associated with images. The association was too subjective to give good results. The work of indexing each image with keywords was easy with small databases but is really unthinkable with large ones. Many methods to try to solve this problem exist. They are generally based on region segmentation, they use local, global or both local and global features computed from the images.

Content-based image retrieval (CBIR) consists in retrieving an image without any "a priori" knowlegde about it. We only use the image itself to match a user request. This request can take several forms: a similar image, a hand-painted approximation (query by example), even a written description of the image. In the latter case, we are faced with the same problem as keywords indexing because the description a user gives is too subjective.

For our research work, an image database from paleontolgy laboratory of *université de Bourgogne*, Dijon, France is used. This database demo is available online on the web at the *université de Bourgogne* website "http://www.u-bourgogne.fr/BIOGEOSCIENCE/ttf2.html" [*]. When up-to-date, this database will contain about 60,000 paleontolgy images of a lot of species from the beginning of life on Earth to the present day.

A review of previous related papers is given in section 2. General methods are presented in section 2.1 while section 2.2 deals with wavelet-based techniques. Our decomposition method using wavelets is explained in section 3. Section 4 gives the indexing technique for transformed images. The method for building a model image is introduced in section 5. The retrieval technique employed is described in section 6. Finally, Section 7 gives a conclusion and overviews future work about our method.

[*]Your computer needs to be Domain Name Service (DNS) declared to access this site.

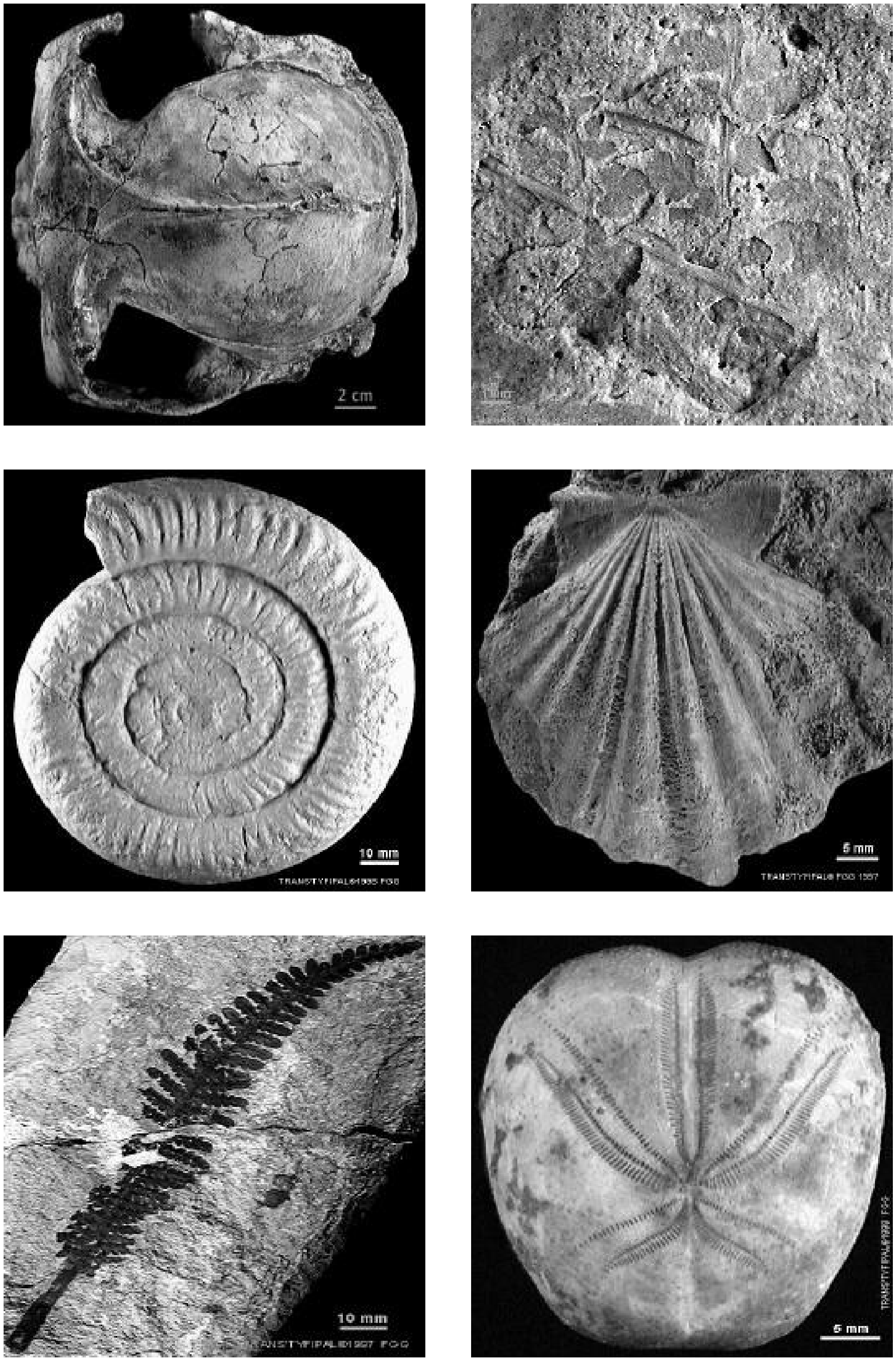

Figure 1. Several examples of TRANS'TYFIPAL images.

2. EXISTING METHODS

2.1. General Methods

Several methods for indexing and retrieving still images from large databases have been published. Different methods give different results. There is no unified technique to test the different existing methods because each method is tested on a different database. The unique way of testing should be to create a large database with a lot of different images and to propose it on the web. Then each method could be tried on this base in order to compare image retrieval systems.

A list of some image retrieval system was given by Pečenović[1] and a review of CBIR systems and methods is given by Vissac[2] . The most popular system is QBIC[3,4] from IBM. The image indexing and retrieval technique is based on texture indexing of image regions. Another system Photobook[5] from MIT Media lab is very efficient for homogeneous images databases. It uses color, texture and shapes features to work. In the Virage system[6] color location and texture can be used with various weights. We could also cite the Chabot system,[7] RetrievalWare at "http://vrw.excalib.com:8015/cst" and Netra at "http://maya.ece.ucsb.edu/Netra/".

This paper proposes a method based on multiresolution decomposition of database images.

2.2. Wavelet-Based Methods

Our approach uses a multiresolution decomposition of images using wavelets. Wavelets were first introduced by Grossman[8] and Morlet as a mathematical tool for analyzing seismic signals. Then the theory was developed by many contributors[9–15] . Today, wavelets are a very powerful mathematical tool used for many signal processing tasks[16] .

Several wavelet based methods for CBIR were published. In their paper, Jacobs,[17] Finkelstein and Salesin use multiresolution analysis to create an index formed upon the indices and signs of the largest-magnitude wavelet coefficients. So they compare the index of the request and the database images using a distance function. Another method based on moments and wavelets was proposed by Mandal,[18] Aboulnasr and Panchanathan. Histograms of the wavelet subbands are used for indexing. Idris[19] and Panchanathan give a method based on wavelet vector quantization in which they compare feature vectors built upon wavelet coefficients. The idea of progressive retrieval is given by Liang[20] and Kuo. Wavelets coefficients are computed at several levels and then they go through each level during retrieval. Stark[21] desribes a multiresolution technique using neural networks for wavelet-texture analysis classification. In his report, Pečenović[22] details a wavelet-packet algorithm to approximate Karunen-Loève Transform on images to index and retrieve them. Do[23] proposes a wavelet maxima moment method where wavelet decomposition is followed by indexing locally maxima wavelet moments. Chen[24] , Li and Chien work with color image segmentation at multiple scales allowing progressive retrieval. As far as we know, none of the previous wavelet decomposition techniques use automatic classification of images in order to build a research tree. Our solution helps users to navigate through the database quickly and simply by choosing the image closest to their request at each level of the tree.

3. MULTIRESOLUTION DECOMPOSITION TECHNIQUE

The multiresolution decomposition technique we use has been introduced by Mallat[14] and gives an approximation image from an original image and one or more detail image(s) at multiple scales. Each scale contains details of the original image.

This technique offers four interesting points for our work:

- Multiresolution decomposition: each image is decomposed into an approximation image and one or more detail image(s) at multiple scales giving us the opportunity to find good parameters representing each family in our database at multiple scales (used for indexing). Each different scale gives different details leading us to use progressive retrieval methods,
- Several wavelets-based compression techniques have been studied in the recent years allowing us to compress our image to reduce our database size ,
- Image watermarking is possible using wavelets decomposition and low-level details information. We can make our images watermarked for copyright reasons,

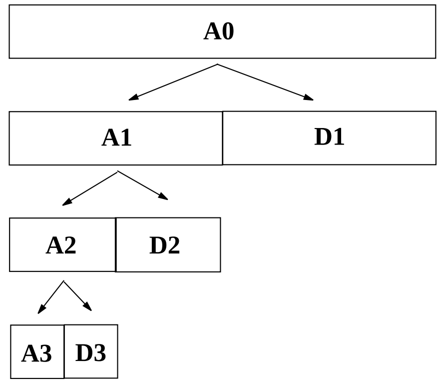

Figure 2. An overview of multiresolution decomposition

- Reconstruction is possible allowing us to store transformed images directly into the database instead of original images. This can be a solution to earn computing time while accessing our database.

In this article, we will focus on the first abovementionned point, leaving compression, watermarking and reconstruction for future work.

A paleontolgy image database called "TRANS'TYFIPAL" is used to test our method. Several images extracted from this base are shown in figure 1.

Our approach is based upon the general idea of multiresolution representation of images. An image is represented at multiple resolutions, each resolution giving fewer details than the previous one. Figure 2 gives a pyramid where the original image A0 is the root. A0 is transformed into an approximation image A1 and one or more detail image(s) D1. The process is iterated and A1 is transformed into A2 and D2. At the end of the process, A3 is the approximation image and D3 is (or are) the detail image(s) of our original image.

A dyadic separable wavelet transform is used to analyze our database images. In this decomposition, each transformed image is a quarter the size of the upper level image. This is important information because we have to work with square decomposable image sizes, for instance 512x512, 256x256, 128x128... This kind of transform offers an approximation image and three detail images: horizontal, vertical and diagonal. An example of this kind of decomposition is shown in figure 3.

This method gives the opportunity to extract parameters at each scale of the decomposition. These parameter values are different from one scale to another allowing to use a progressive retrieval scheme. The decomposition goes from high levels to low levels, in our example from A0 to A3. When searching the database, the low-level indexes (lowest index size) are used first. Then, the more we want to refine the higher the level. With this way of searching one can force a search time for our system. If the user wants quick response then only low-level indexes are used, if not, (time consuming) high level indexes are used.

4. INDEXING

The purpose of indexing is to speed up the process of retrieving images. Instead of working directly with images (a long and fastidious task), the idea is to use a reduced set of parameters characterizing the images.

In this article, only gray-level images are used for three reasons:

- "TRANS'TYFIPAL" images often come from the earth or far down the ocean, so their colors have been altered by millions of years under the ground or under water.
- Due to a bad conservation state, some of the specimens were artificially colored before photography.
- A red ammonite is an ammonite. The color of the specimen does not matter for our study.

Figure 3. An example of 3-level multiresolution analysis on a TRANS'TYFIPAL image. Horizontal, vertical and diagonal details are visible at each different scale.

The algorithm is simple as it works with square constant-sized images. For each image, a four-level wavelet transform is computed. Haar wavelets and spline wavelets are the wavelet families chosen. The former because they are fast and easy to compute, the latter because their localization is better. Then for each level of computed details, ten normalized parameters are computed. A vector made of one hundred and twenty parameters is obtained. This vector and the low resolution approximation subimage make the index.

The computed parameters are based on wavelet coefficients:

- maximum value
- minimum value
- mean value
- normalized energy
- inertia moments ratio
- texture heterogeneity
- texture entropy
- histogram maximum value
- histogram minimum value
- histogram mean value

Progressive retrieval is made possible by the different levels found in the index.

5. BUILDING A MODEL

For each level, all the images are classified in the hyperspace of parameters using the "dynamic clouds" algorithm. We ask the algorithm to classify each image in four families at each level of the tree. An image is then labeled with the number of its class. In each class, we decide the model image of this class to be the closest to the gravity center of the class. This model image is then the root for our tree. So four images representing four classes are used at the

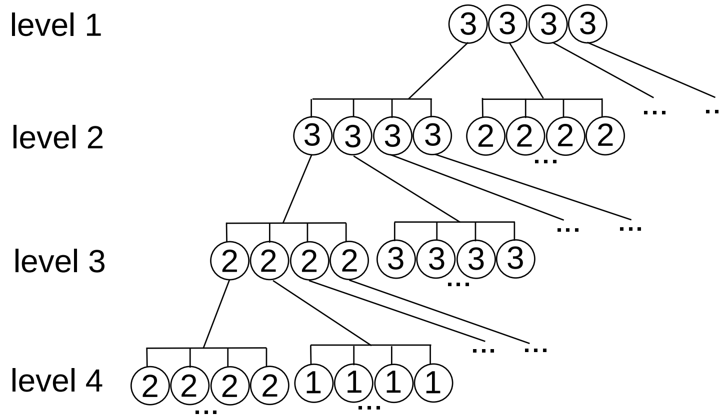

Figure 4. A four-level tree built upon a three-scale multiresolution analysis. Each node of the tree is labeled with scale index used.

root of the tree. At the next level, for each class, another classification is done. At this level, four other images are obtained which are the model of level two. The process is reiterated to build the tree. When the classification is not possible with j level parameters, the classification is computed using j+1 level parameters. The criteria to determine whether the classes are separable is that the inter-class distance must be at least twice the standard deviation of the class.

An example of a built tree is shown on figure 4. The root of the tree contains four model images which are the closest images to the gravity center of the first four classes. At the root, only third scale index is used for classification. Then, the process is reiterated and the first class is classified at scale three at the lower level. In this example,it is assumed that the algorithm is not able to create four classes with third scale parameters, so the next level of the tree uses second-level index. At this level of the tree, the first class is decomposed using second-scale parameters. But the second class is decomposed using the first-scale parameters.

The classification occurs until a reduced number of images are present in each class typically three to ten images or until it is not possible to create four classes with scale-one parameters.

6. RETRIEVING IMAGES

When searching our database, a user goes through the built tree, selecting with his mouse images similar to those of his request. The four root models of our tree are proposed to the user who chooses one of them. Again, four model images of the previous class are shown. The user can choose and navigate through these images to find what he or she is looking for.

The full process is shown in figure 5. For each image in the database, a wavelet transform is computed. This leads to the extraction of several parameters at multiple scales. The index is created from these parameters. Then the images are classified using the “dynamic clouds” algorithm. The research tree in which the model images (closest to the gravity center of the class) represent the classes is built. The user navigates the database by clicking the images of the tree, looking for an image similar to the request.

7. CONCLUSION AND PERSPECTIVES

In this paper, a research study about CBIR has been introduced. As far as we know, the idea of proposing a research tree based upon wavelet decomposition of images is new. The building of a model image allowing the user to navigate the database by clicking simplifies the approach of CBIR systems. A lot of studies are possible to enhance the results. An interesting study would be to try several wavelet families during decomposition to test the response of the system. Different color spaces typically RGB and HSV could give better results than greyscale images. Another criterion of inter-class distance could be used during the building of the tree. Another set of parameters could be chosen to

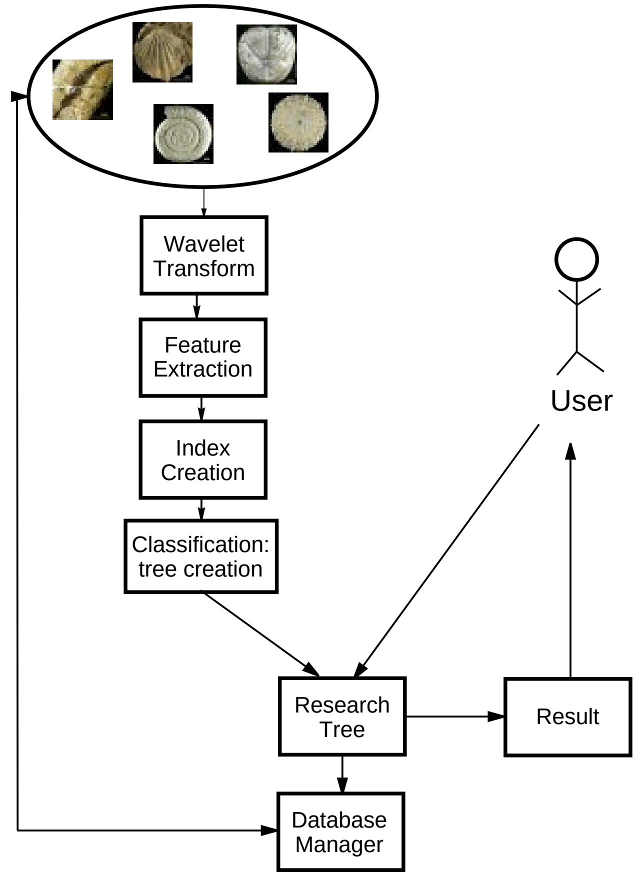

Figure 5. Overview of the studied CBIR system

better represent images. Weighted parameters could be an interesting approach to enhance the retrieving power of the method. For each class, the model image could be the center-distance-weighted sum of the images of the class.

A lot of work has to be done to prepare future wavelets-based CBIR systems.

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