INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH & DEVELOPMENT

ISSN: 2278 – 0211 (Online)

Content Based Image Retrieval Using Fast 2D Wavelet Transform

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Abstract:
Adaptive wavelet-based image characterizations have been proposed in Existing work for content-based image retrieval (CBIR) applications. In this application, the same wavelet basis was used to characterize each query image. This wavelet basis was tuned to maximize the retrieval performance in a training data set. But here a different wavelet basis is used to characterize each query image. A regression function, which is tuned to maximize the retrieval performance in the training data set, is used to estimate the best wavelet filter, i.e., in terms of expected retrieval performance, for each query image. A simple image characterization, which is based on the standardized moments of the wavelet coefficient distributions, is presented. An algorithm is proposed to compute this image characterization almost instantly for every possible separable or no separable wavelet filter. Therefore, using a different wavelet basis for each query image does not considerably increase computation times. On the other hand, significant retrieval performance increases were obtained in a medical image data set, a texture data set, a face recognition data set, and an object picture data set. This additional flexibility in wavelet adaptation paves the way to relevance feedback on image characterization itself and not simply on the way image characterizations are combined.

Key words: *Content-based image retrieval CBIR), relevance feedback, wavelet adaptation, wavelet transform.*

1.Introduction

Content-based image retrieval (CBIR), also known as query by image content (QBIC) and content-based visual information retrieval (CBVIR) is the application of computer vision techniques to the image retrieval problem, that is, the problem of searching fordigital images in large databases. (see this survey for a recent scientific overview of the CBIR field).Content based image retrieval is opposed to concept based approaches (see concept based image indexing).

"Content-based" means that the search will analyze the actual contents of the image rather than the metadata such as keywords, tags, and/or descriptions associated with the image. The term 'content' in this context might refer to colors, shapes, textures, or any other information that can be derived from the image itself. CBIR is desirable because most web based image search engines rely purely on metadata and this produces a lot of garbage in the results. Also having humans manually enter keywords for images in a large database can be inefficient, expensive and may not capture every keyword that describes the image. Thus a system that can filter images based on their content would provide better indexing and return more accurate results.

In such a situation, it is difficult for managers and users of image collections to make informed decisions about the value of CBIR techniques to their own work. With this in mind, the JISC Technology Applications Programme has commissioned the Institute for Image Data Research, University of Northumbria, and the Manchester Visualization Centre, University of Manchester, to conduct a detailed investigation into the potential of CBIR technology. The project consists of several parts:

- a report on the current state of the art in CBIR within the UK (this document);
- an evaluation of existing CBIR software packages;
- an investigation of user experience of CBIR technology through a series of pilot applications;
- a programme of publications, workshops and seminars to raise awareness of CBIR in the UK higher education community.

The effectiveness of all current CBIR systems is inherently limited by the fact that they can operate only at the primitive feature level. None of them can search effectively for, say, a photo of a dog – though some semantic queries can be handled by specifying them in terms of primitives. A beach scene, for example, can be retrieved by specifying large areas of blue at the top of the image, and yellow at the bottom. There is evidence that

combining primitive image features with text keywords or hyperlinks can overcome some of these problems, though little is known about how such features can best be combined
for retrieval.

Our conclusion is that, despite its current limitations, CBIR is a fast-developing technology with considerable potential, and one that should be exploited where appropriate. The report's specific recommendations are as follows:

1.2.To Users And Managers Of Image Collections

- Managers of specialist collections such as fingerprints or trademark images should be encouraged to investigate possible adoption of CBIR technology in the near future.
- Managers of video libraries should investigate the possibility of using a proprietary video asset management package.
- Managers of general-purpose image collections should be encouraged to keep a watching brief on developments in CBIR.

1.3.To Software Developers Or Information Providers With Products Designed To Handle Images, But Which Currently Lack CBIR Capabilities

- Firms with products or services in specialist areas such as fingerprints or trademark images should investigate the possibility of adding CBIR technology to their products in the near future.
- Providers of general-purpose multimedia need to keep a watching brief on developments in CBIR, particularly relating to hybrid text/image feature indexing and cross-media retrieval.

1.4.To UK Government Agencies

- Funding agencies should consider declaring CBIR research a priority area, as has been done in the USA, and to a lesser extent in the European Community. Topics particularly worth supporting, in the expectation that they will lead to useful results in the long term, include new approaches to semantic image retrieval, cross-media indexing, interface design, studies of image seeking behaviour and use, and evaluation of system effectiveness.

- Agencies concerned with technology transfer or dissemination of best practice in fields which could potentially benefit from CBIR should consider sponsoring programmes to raise awareness of CBIR technology among leading practitioners in these fields.

1.5.To JISC

- Further pilot studies of CBIR should be undertaken, with a view to identifying the benefits and costs of CBIR technology, and the specific types of user most likely to benefit.
- Provided such benefits can in fact be identified, a further programme to raise awareness of the technology and its benefits should be undertaken.
- Again, provided benefits from the use of CBIR can be demonstrated, large-scale trials of the effectiveness of different ways of delivering CBIR should be undertaken.
- Since the USA is likely to remain the main source of research activity in the CBIR field, every effort should be made to encourage further co-operation between the UK and USA in this area. In particular, JISC should continue to participate actively in the NSF International Digital Libraries Program.

2.Methodology

Over the last decades, the wavelet transform has become a major image characterization tool. One advantage of the wavelet transform over alternative methods is the ability to tune the underlying wavelet basis to users' needs, e.g., to optimize compression, classification, or retrieval performances. Originally, wavelet adaptation was mostly used to approximate a reference signal up to a desired scale. With the advent widespread, both for separable and no separable wavelet transforms. Recently, we have introduced two adaptive wavelet-based image characterizations which have been successfully applied to different problems.One possible application of wavelet adaptation is content based image retrieval (CBIR), which is an increasingly popular discipline in computer science The goal of CBIR is to automatically select, i.e., in a reference data set, images that resemble a query image. Image characterizations are used to catch similarities between images. Modern retrieval systems usually rely on machine learning to bridge the semantic gap between low-level image characterizations The proposed image characterization is lighter: It is simply based on standardized moments of the wavelet coefficient distribution. In order to easily characterize again each reference image, we propose to compute a characterization map as follows: 1) exact image characterizations are computed for a limited number of wavelet filters of given support and 2) approximate characterizations can be computed almost instantaneously for every possible wavelet filter of equal support. Such characterization maps can be computed indifferently for separable or no separable wavelet filters. Due to these characterization maps, characterizing an image again using a different wavelet filter does not involve reprocessing the image. In conclusion, using a different wavelet filter for each query image in a CBIR application is now possible.

2.1.Block Diagram Of Compression Algorithm

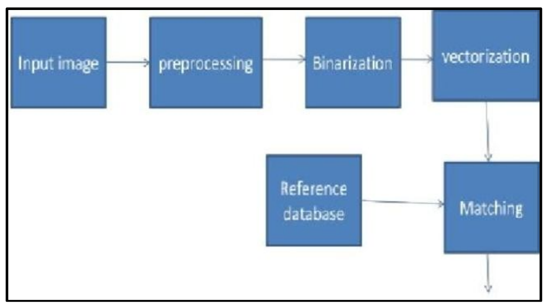

Figure 1: A schematic diagram of the decompression scheme

A Figure 1 shows the schematic diagram of the decompression scheme. The black arrows indicate, respectively, the information flow of the decompression process and the information flow of the preparation of training images.

2.2.Characterizing One Image With A Given Wavelet Filter

Let I = (Ii,j)i=0,…….M-1,J=0,…N-1 be an image of size M×N Pixels.Let W=(Kw,l)k=-
K,…K,l=-L,…L be a wavelet filter of support(2K+1)×(2L+1). By definition of a wavelet filter, the following relation holds for W[16].

I propose to characterize the distribution of detail coefficients (X i, j,s)i=0,….M-1,j=0,…N-1 in with standardized moments. In the particular case of texture images, Wouwer et al. have shown that the distribution of detail coefficients at any analysis scale can be modeled meaningfully by an unscrewed zero-mean generalized Gaussian function; we extended this observation to a more general class of images in previous works.

2.3.Wavelet Filter Space

Letwk,l denote the space of all wavelet filters of support(2K+1) × (2L+1). Let denote its dimension. Because the central coefficient of each filter w € Wk,l is constrained by (1), (i.e.,). D= (2K+1) × (2L+1).-1

2.4.Characterization Map And Characterization

2.4.1.<u>Derivative Maps</u>

For wavelet adaptation purposes, we propose to compute the characterization of for a given analysis scale and each filter . The resulting set of characterizations is referred to as the characterization map of (given , , and). For wavelet adaptation purposes, it is also useful to compute the first-order derivatives of each characterization. The resulting sets of characterization derivatives are referred to as the characterization derivative maps of . Since characterizing an image with a given wavelet filter can be time-consuming (the complexity is in ;

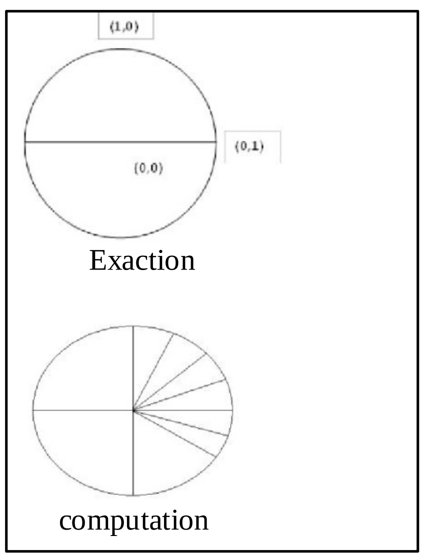

Figure 2:Exaction, computation, Approximatecomputation

Fig 2. Shows the union of these sets: Its cardinal is therefore If , then the key wavelet filters are selected exactly uniformly in one half of the unitsphere. The second step is to approximate the characterizations and characterization derivatives in

$$\|w\|_2 = 1$$

this set, image characterizations are approximated by Taylor expansions; the closest key wavelet filter plays the role of (see Section III-C). Taylore

2.4.2.Image Retrieal

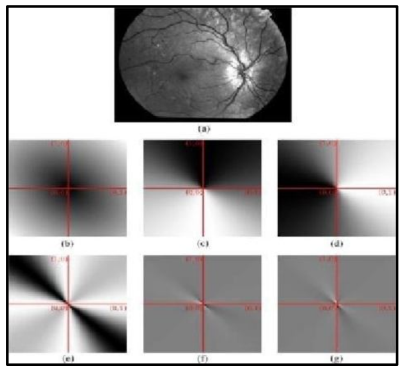

Figure 3: Example of characterization map, in (b) and (e), and of characterizationderivative aps, in (c), (d), (f) and (g), obtained for image (a) at the analysis [in (b)], (e)],or one of their derivatives. In (b) and (e), black means 0. In (c), (d), (f), and(g), medium gray means 0.

Fig 3.shows the let be a query image and be a data set of reference images. In this section, characterization maps are used to rank images in increasing order of distance to . Then, the first images, which are noted , are retrieved. In this paper, the goal is to retrieve a small set of highly relevant images. that belong to the same category as . If,on the contrary, one would like to retrieve all potentially relevant images in the reference data set, then the recall at a large should be maximized instead . Achieving high precision is challenging when the number of categories is high or when the semantic

2.4.3.Experiments And Screenshots

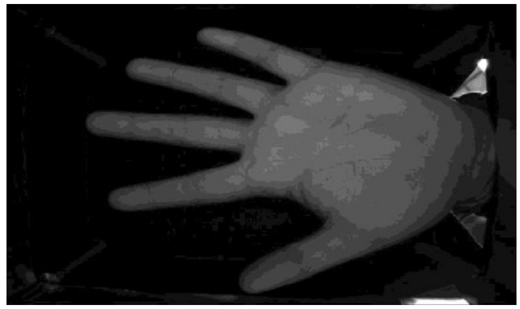

Figure 2: Input Image

Fig. 2.shows the input image . The input image is a gray image. It is of default size 768*768. For our convenience, the input image is resized to 512*512.

2.4.4.Output Image

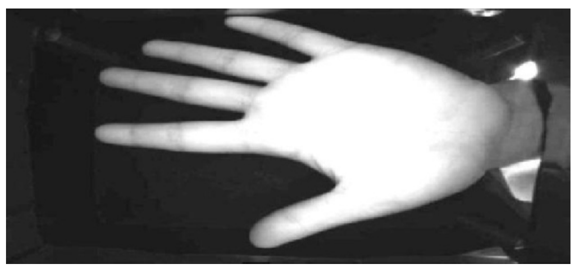

Figure 3: Output image

Fig. 3. Output image shows the retreival image of the input image.

3.Conclusion & Future Enhancements

3.1.Conclusion

I proposed a method to two kinds of generic wavelet-based image signatures, with associated distance measures, have been evaluated in a CBIR system. They take advantage of the flexibility inherent in the wavelet transform framework to adapt the system to any specialized database. In particular, a way to adapt the wavelet transform to a high-level criterion, within the lifting scheme framework, is proposed in this paper. It makes it possible to generate any wavelet transform, respecting the biorthogonality relations, and with a desired number of vanishing moments. A controlled random search, based on a genetic algorithm, is then performed in the predict and update filter space in order to find the optimal wavelet transform, and a similar search is performed in the distance weight vector space in order to maximize the precision of the system.

3.2.Future Enhancements

To improve the quality of astrophysical images produced by means of the generalized least square (GLS) approach. And achieve better PSNR result for compressed astrophysical images. This study paves the way to efficient relevance feedback on image features hemselves, which should enable interactive image search with higher performance.

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