Distributed Visual Information Management in Astronomy

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Abstract

Among the many interesting computational problems posed by observational astronomy, broad aspects of visual information management are crucial. In this regard observational astronomy "collaboratories" provide important testbeds for other fields serving less well-defined communities. Telemedicine, Earth observation, and graphic art and design, come to mind. We will review issues related to large image visualization in astronomy, and a recently developed toolset for this purpose. Resolution scale is central here. Resolution scale offers one way to address the long-term data storage problem, and we will review recent developments in this area. To support image database querying, we define multiple resolution information and entropy. We show how these are closely related to compression rate. We discuss the use of these concepts in image database querying.

1 Introduction

The quantity of astronomical data is increasing at a growing rate. In part this is due to very large digitized sky surveys in the optical and near infrared, which in turn is due to the development of digital imaging arrays such as CCDs (charge-coupled devices). The size of digital arrays is also continually increasing, pushed by the demands of astronomical research for ever larger quantities of data in ever shorter time periods. Currently, projects such as the European DENIS and American 2MASS infrared sky surveys, or the Franco-Canadian MegaCam Survey and the American Sloan Digital Sky Survey, will each produce of the order of 10 TB (tera bytes) of image data. The American LSST, to be commissioned in 2007–2008, will produce about 5 PB (peta bytes) of data per year in surveying the skies. The routine and massive digitization of photographic plates has been made possible by the advent of automatic plate scanning machines (MAMA, APM, COSMOS, SuperCOSMOS, APS, PMM, PDS) [11]. These machines allow for digitization of the truly enormous amount of useful astronomical data represented in a photograph of the sky, and they have opened up the full potential of large area photographic sky surveys.

The straightforward transfer of such amounts of data over computer networks becomes cumbersome and in some cases practically impossible. Transmission of a high resolution Schmidt plate image over the Internet would take many hours. Facing this enormous increase in pixel volume, and taking into account the fact that catalogs (i.e., relational tables) produced by extraction of information from the pixels can always be locally wrong or incomplete, the needs of the astronomer follow two very different paths:

- The development of web technology creates the need for fast access to informative pixel maps, which are more intuitively understandable than the derived catalogs.

and photometry (i.e., accumulated flux data), or effective redetection of missed objects.

2 Compression Strategies

Based on image type and application, different compression strategies can be used [7, 10]:

1. Lossy compression: in this case compression ratio is relatively low (< 5).
2. Compression without visual loss. This means that one cannot see the difference between the original image and the decompressed one. Generally, compression ratios between 10 and 20 can be obtained.
3. Good quality compression: the decompressed image does not contain any artifact, but some information is lost. Compression ratios up to 40 can be obtained in this case.
4. Fixed compression ratio: for some technical reason or other, one may decide to compress all images with a compression ratio higher than a given value, whatever the effect on the decompressed image quality.
5. Signal/noise separation: if noise is present in the data, noise modeling can allow for very high compression ratios just by including filtering in wavelet space during the compression.

According to the image type and the selected strategy the optimal compression method may vary. A major interest in using a multiresolution framework is to get, in a natural way, the possibility for progressive information transfer.

Point number 5 above is of particular relevance in the context of support for a region of interest in an image. The JPEG 2000 standard, for example, supports a region of interest based on a mask [2, 5]. Through noise analysis, we have a natural and automated way to define the mask. Furthermore, our noise analysis is carried out at each resolution scale. Within the mask region, encoding is used which guarantees valid scientific interpretation: this is based on acceptable pixel value precision on decompression. Outside the mask region wavelet coefficient filtering can go as far as zeroing the coefficients, i.e., applying infinite quantization.

Using this principle leads to outstanding results. We have found, for example, that compression rates of close to 300:1 are possible with – and this is a crucial consideration – guaranteed fidelity to scientifically-relevant properties of the image (astrometry, photometry, and faint features). JPEG, by way of contrast, rarely does better than about 40:1.

In the case of JPEG, various studies confirm that beyond a compression rate of 40:1 this method of compression, when used on 12 bit/pixel images, gives rise to blocky artifacts. For the pyramidal median transform (a pyramidal multiresolution algorithm based on the median transform, which is implemented in an analogous way to a wavelet transform: see [7, 16]) the reconstruction artifacts appear at higher compression rates, beyond a rate of 260 in the particular case of our images. Figs. 1 and 2 allow the visual quality of the two methods to be compared. A subimage is shown here from a 1024×1024 image of the globular cluster M5, extracted from an ESO (European Southern Observatory) Schmidt photographic plate (numbered 7992v) and digitized with the CAI-MAMA (Centre for Image Analysis – Automatic Measuring Machine for Astronomy, Observatoire de Paris, Paris, France).

Consider the usage of a rigorously lossless wavelet-based compressor, above and beyond the issues of economy of storage space and of transfer time. Sweldens' lifting scheme [19] provides a convenient algorithmic framework for many wavelet transforms. The low-pass and band-pass operations are replaced by predictor and update operators at each resolution level, in the construction of the wavelet transform. When the input data consist of integer values, the wavelet transform no longer consists of integer values, and so we redefine the wavelet transform algorithm to face this problem. The predictor and update operators use a floor truncation function. The lifting scheme formulas for prediction and updating allow this to be carried out with no loss of information.

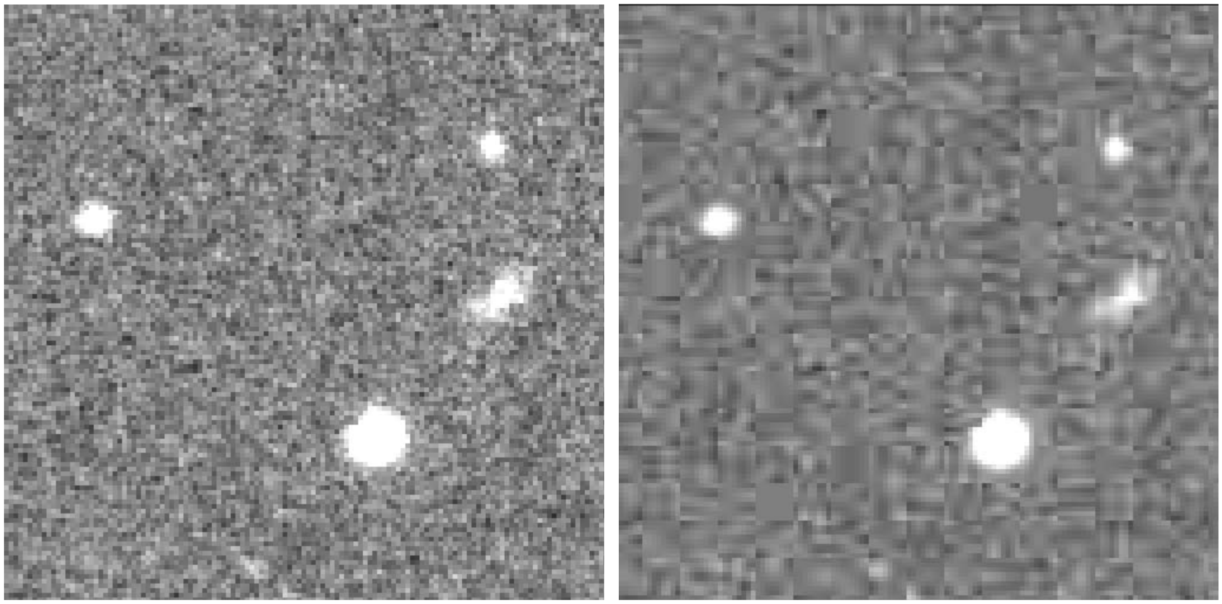

Figure 1: Left: Original image, which is a subimage extracted from a 1024×1024 patch, extracted in turn from the central region of ESO7992v. Right: JPEG compressed image at 40:1 compression rate.

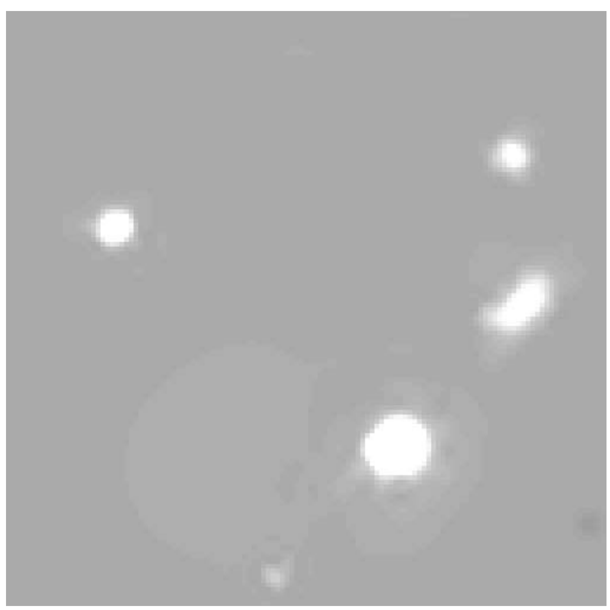

Figure 2: Pyramidal median transform compressed image at 260:1 compression rate.

appealing property that lower resolution versions of an image are *exactly* two-fold rebinned versions of the next higher resolution level (see [8]). For aperture photometry and other tasks, lower level resolution can be used to provide a partial analysis. A low resolution level image can be used scientifically since its "big" pixels contain the integrated average of flux covered by them. The availability of efficiently delivered low resolution images can thus be used for certain scientific objectives. This opens up the possibility for an innovative way to analyze distributed image holdings. We will return to this issue below.

3 Image Visualization Based on Compression

With new technology developments, images furnished by detectors are ever larger. For example, current astronomical projects are beginning to deal with images of sizes larger than 8000 by 8000 pixels (VLT 8k $\times$ 8k, MegaCam and Vista 16k $\times$ 16k). A digitized mammogram film may lead to images of about 5k $\times$ 5k. In addition to data compression, and progressive decompression, we have to consider a third concept, region of interest. Images are becoming so large it is impossible to display them in a normal window (typically of size 512 $\times$ 512), and we need to have the ability to focus on a given area of the image at a given resolution. To move from one area to another, or to increase the resolution of a part of the area is a user task, and is a new active element of the decompression.

The principle of our LIVE, Large Image Visualization Environment, toolset based on multiresolution data structure technology, is to support the following:

- Full image display at a very low resolution.
- Image navigation: the user can go up (the quality of an area of the image is improved) or down (return to the previous image). Going up or down in resolution implies a four-fold increase or decrease in the size of what is viewed.

Fig. 3 illustrates this concept. A large image (say 4000 $\times$ 4000), which is compressed by blocks (8 $\times$ 8, each block having a size of 500 $\times$ 500), is represented at five resolution levels. The visualization window (of size 256 $\times$ 256 in our example) covers the whole image at the lowest resolution level (image size 250 $\times$ 250), but only one block at the full resolution (in fact between one and four, depending on the position in the image). The LIVE concept consists of moving the visualization window into this pyramidal structure, without having to load into memory the large image. The image is first visualized at low resolution, and the user can indicate (using the mouse) which part of the visualized subimage it is wished to zoom on. At each step, only wavelet coefficients of the corresponding blocks and of the new resolution level are decompressed.

4 Decompression by Scale and by Region

Support of the transfer of very large images in a networked (client-server) setting requires compression and prior noise separation. Noise separation aids greatly in compression, because noise is axiomatically not compressible.

A prototype has been developed with a Java client [9], and another prototype [4] allows the visualization of large images with the widely used SAO DS9 software (available from the Smithsonian Astrophysical Observatory at http://hea-www.harvard.edu/RD/ds9, see [6]).

We examined compression performance on large numbers of astronomy images. Consider for example a 12451×8268 image from the CFH12K detector at the CFHT (Canada-France-Hawaii Telescope), Hawaii. A single image is 412 MB. Given a typical exposure time, say a few minutes or less, one can calculate quickly the approximate amount of data expected in a typical observing night.

Some typical computation time requirements follow. Using denoising compression, we compressed the CFH12K image to 4.1 MB, i.e. less than 1% of its original size. Compression took

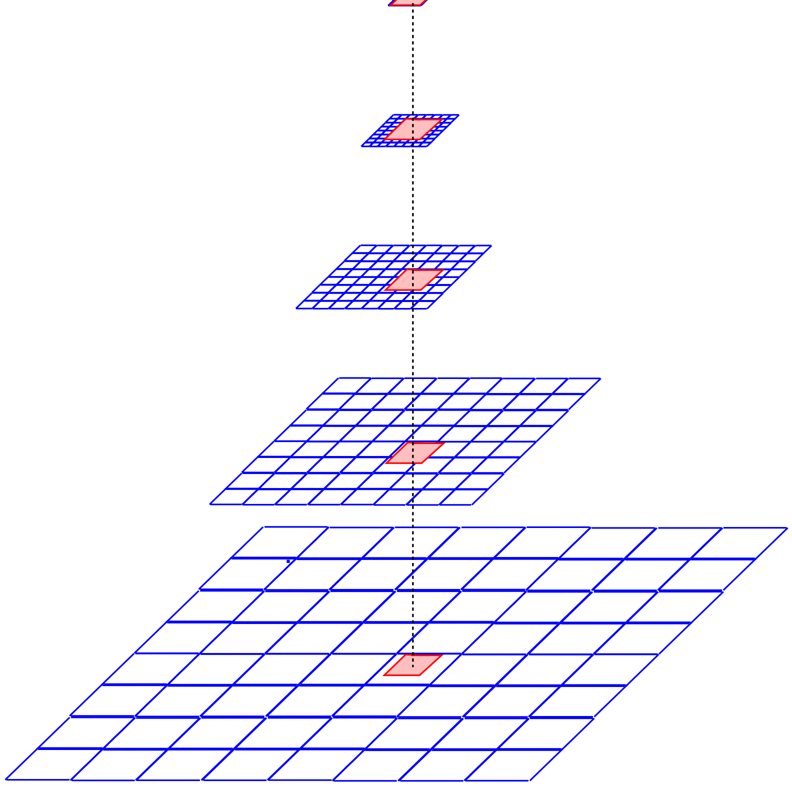

Figure 3: Example of large image, compressed by block, and represented at five resolution levels. At each resolution level, the visualization window is superimposed at a given position. At low resolution, the window covers the whole image, while at the full resolution level, it covers only one block.

789 seconds on an Ultra-Sparc 10. Decompression to the fifth resolution scale (i.e., dimensions divided by 2^5) took 0.43 seconds. For rigorously lossless compression, compression to 97.8 MB, i.e. 23.75% of the original size, took 224 seconds, and decompression to full resolution took 214 seconds. Decompression to full resolution by block was near real-time.

A user interface was developed [4] for images compressed by the software package MR/1 [9], which comes as a plug-in for the image viewer SAO-DS9. This interface allows the user to load a compressed file and to choose not only the scale, but also the size and the portion of image to be displayed, resulting in reduced memory and processing requirements. Astrometry and all SAO-DS9 functionality are still simultaneously available.

- Compression: The compression and decompression tools are part of the MR1 package [9]. Wavelet, pyramidal median, and lifting scheme are implemented, with lossy or lossless options. The final file is stored in a customized format (with the extension .fits.MRC).

- Image viewer: They are many astronomical image viewers. We looked at JSky (because it is written in Java) and SAOImage-DS9. The latter was selected: it is well maintained, and for the programmer it is simpler. DS9 is a Tk/Tcl application which utilizes the SAOTk widget set. It also incorporates the new X Public Access (XPA) mechanism to allow external processes to access and control its data, and graphical user interface functions.

- Interface: DS9 supports external file formats via an ascii description file. It worked with the MRC format, but it enables only one scale of the image to be loaded. The selected solution was a Tcl/Tk script file which interacts with XPA. Tcl/Tk is recommended by the SAO team and is free and portable.

  This interface enables the user to

– select the maximum size of the displayed window,

– zoom on a selected region (inside the displayed window), and

– unzoom.

The Tcl/Tk script file with DS9 and the decompressed module has been used on Solaris (Sun Microsystems Sparc platform), Linux (Intel PC platform) and Windows NT, 2000 (with some tuning), and can also work on HP-UX, ALPHA-OSF1. On a 3-year old PC, the latency is about one second.

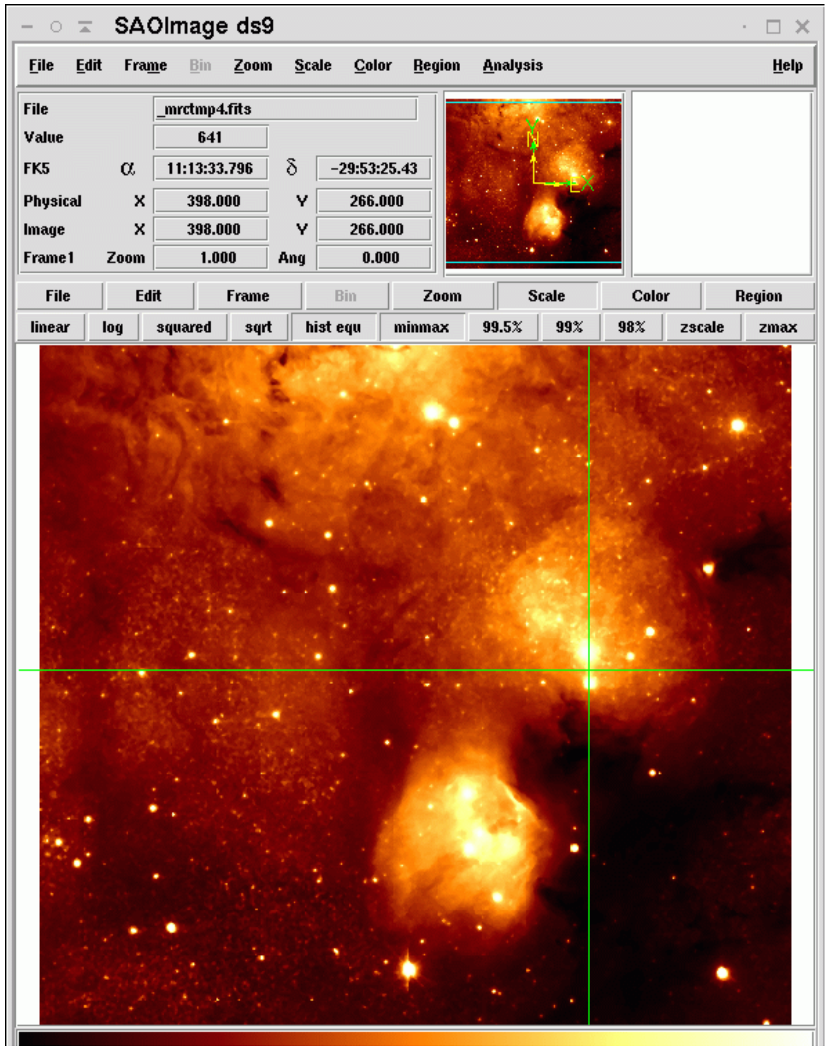

Figure 4: SAO DS9 with the XLIVE-DS9 user interface.

Fig. 4 shows an example of operation. The image is due to J.-C. Cuillandre, and shows a five minute exposure (five 60-second dithered and stacked images), R filter, taken with CFH12K wide field camera (100 million pixels) at the primary focus of the CFHT (Canada-France-Hawaii Telescope, Hawaii) in July 2000. Shown is a rich zone of our Galaxy, containing star formation regions, dark nebulae (molecular clouds and dust regions), emission nebulae, and evolved stars.

5 Resolution Scale in Data Archives

Unlike in Earth observation or meteorology, astronomers do not want to interpret data and, having done so, delete it. Variable objects (supernovae, comets, etc.) prove the need for as-quantity of data which is now collected. The only basis for selective choice for what must be kept long-term is to associate more closely the data capture with the information extraction and knowledge discovery processes. We have got to understand our scientific knowledge discovery mechanisms better in order to make the correct selection of data to keep long-term, including the appropriate resolution and refinement levels.

Long-term storage of astronomical data, we have already noted, is part and parcel of our society's memory. With the rapid obsolescence of storage devices, considerable efforts must be undertaken to combat social amnesia.

Recent research in data warehousing is now beginning to address this problem of the need for long-term data storage, constrained by the growing quantity of data available. Skyt and Jensen [12] discuss the replacing of aging low-interest detailed data with aggregated data. Traditional databases are append-only, and deletion is a logical rather than a physical operation. A new approach is based on a temporal vacuuming specification where access consists of both a removal specification part and a keep specification part. Removal is carried out in an asynchronous or lazy manner. A vacuumed temporal database is one defined by a set of temporal relations which have been vacuumed according to the vacuuming specification.

Thus far, so good: we have a conceptual framework for keeping aggregated data in the long term, based on an aggregation specification. An example discussed in [12] is web click-stream data, where the aggregation is based on access hits. In astronomy imaging we have already noted the potential of the Haar wavelet transform using a lifting scheme implementation to provide functionality for data aggregation. Aggregated flux uses "big" pixels. Local flux conservation is guaranteed.

The formal application of data aggregation to the vacuuming of scientific databases has yet to be used in practice.

6 Multiple Resolution Information and Entropy

Compression and resolution ought to be inherently linked to information content, and consequently to entropy. The latter provide quality criteria (e.g., the question: Is one compression result better than another?) and also inherent limits to data coding. We will look first of all at a link which we have developed between compression and entropy. In later sections, we will look at how image information content can be useful for retrieval of image information.

In [17] and in [14], a theory of multiscale entropy filtering was introduced. This theory was based on the following principles.

1. The signal or image is modeled as a realization (sample) from a random field, which has an associated joint probability density function (PDF). Entropy is computed from this PDF, not directly from the signal or image pixel intensities themselves.

2. A basic "vision model" is used, which takes a signal, X, as a sum of components: $X = S + B + N$, where S is signal proper, B is background, and N is noise.

3. Extending this decomposition further, entropy is further decomposed by resolution scale.

Point 3 is based on defining the entropy in wavelet transform space. The DC component (or continuum) of the wavelet transform provides a natural definition of signal background. A consequence of taking resolution scale into account is that signal correlation is thereby accounted for. Point 2 rests on a sensor (or data capture) noise model.

For the resolution scale related decomposition, we have the following. Denoting h the information relative to a single wavelet coefficient, we define

$$H(X) = \sum_{j=1}^{l} \sum_{k=1}^{N_j} h(w_{j,k}) \tag{1}$$

j, and $p(w_{j,k})$ is the probability that the wavelet coefficient $w_{j,k}$ is due to noise. The smaller this probability, the more important will be the information relative to the wavelet coefficient. For Gaussian noise we get

$$h(w_{j,k}) = \frac{w_{j,k}^2}{2\sigma_j^2} + \text{Const.} \tag{2}$$

where σ_j is the noise at scale j (in the case of a (bi-) orthogonal wavelet transform using an L^2 normalization, we have $\sigma_j = \sigma$ for all j, where σ is the noise standard deviation in the input data).

Multiscale entropy can be introduced into filtering and deconvolution, and by implication feature and faint signal detection (see [14]).

A range of examples was considered in [17, 14] based on simulated signals, the widely used Lena image, and case studies from astronomy. In [15], this work was extended to include (i) a range of noise models other than Gaussian and (ii) the role of vision models in this framework. In the case of astronomy, [18] looked at multiple band data, based on the Planck orbital observatory (a European Space Agency mission, planned for 2007, to study the cosmic background radiation), and introduced a joint wavelet and Karhunen-Loève transform (the WT-KLT transform) to handle cross-band correlation when filtering such data. In [18] we also look at background fluctuation analysis in astronomy, where we may not be able to observe the presence of astronomical sources, but we know they are there (for instance, due to observations in other parts of the electromagnetic spectrum).

7 Multiscale Entropy as a Measure of Relevant Information

Since the multiscale entropy extracts the information from the signal only, it was a challenge to see if the astronomical content of an image was related to its multiscale entropy.

For this purpose, we studied the astronomical content of 200 images of 1024 × 1024 pixels extracted from scans of 8 different photographic plates carried out by the MAMA digitization facility (Institut d'Astrophysique, Paris, France) and stored at CDS (Strasbourg Data Center, Strasbourg Observatory, France). We estimated the content of these images in three different ways:

1. By counting the number of objects in an astronomical catalog (USNO A2.0 catalog) within the image. The USNO (United States Naval Observatory) catalog was originally obtained by source extraction from the same survey plates as we used in our study.

2. By counting the number of objects estimated in the image by the Sextractor object detection package [1]. As in the case of the USNO catalog, these detections are mainly point sources (i.e. stars, as opposed to spatially extended objects like galaxies).

3. By counting the number of structures detected at several scales using the MR/1 multiresolution analysis package [9].

Fig. 5 shows the results of plotting these numbers for each image against the multiscale signal entropy of the image. The best results are obtained using the MR/1 package, followed by Sextractor and then by the number of sources extracted from USNO. The latter two basically miss the content at large scales, which is taken into account by MR/1. Unlike MR/1, Sextractor does not attempt to separate signal from noise.

Sextractor and multiresolution methods were also applied to a set of CCD (charge coupled device, i.e. digital, as opposed to the digitized photographic plates used previously) images from CFH UH8K, 2MASS and DENIS near infrared surveys. Results obtained were very similar to what was obtained above. This lends support to (i) the quality of the results based on MR/1, which take noise and scale into account, and (ii) multiscale entropy being a good measure of content of such a class of images.

compression rate of an image which we can obtain by multiresolution techniques. By optimal compression rate we mean a compression rate which allows all the sources to be preserved, and which does not degrade the astrometry (object positions) and photometry (object intensities). Louys et al. [7] have estimated this optimal compression rate using the compression program of the MR/1 package.

Fig. 6 shows the relation obtained between the multiscale entropy and the optimal compression rate for all the images used in our previous tests, both digitized plate and CCD images. The power law relation is obvious thus allowing us to conclude that:

- The compression rate depends strongly on the astronomical content of the image. We can then say that compressibility is also an estimator of the content of the image.
- The multiscale entropy confirms, and indeed allows us to predict, the optimal compression rate of the image.

8 Multiscale Entropy for Image Database Querying

We have seen that information must be measured from the transformed data, and not from the data itself. This is so that a priori knowledge of physical aspects of the data can be taken into account. We could have used the Shannon entropy (perhaps generalized, cf. [13]) to measure the information at a given scale, and derive the bins of the histogram from the standard deviation of the noise, but for several reasons we thought it better to directly introduce noise probability into our information measure. This leads, for Gaussian noise, to a very physically meaningful relation between the information and the wavelet coefficients (eqn. 2): information is proportional to the energy of the wavelet coefficients normalized by the standard deviation of the noise. Secondly, this can be generalized to many other kinds of noise, including such cases as multiplicative noise, non-stationary noise, or images with few photons/events. Finally, experiments have confirmed that this approach gives good results.

In the work presented in section 7 which was related to the semantics of a large number of digital and digitized photographic images, we took already prepared – external – results, and we also used two other processing pipelines for detecting astronomical objects within these images. Therefore we had three sets of interpretations of these images. We then used Multiscale Entropy to tell us something about these three sets of results. We found that Multiscale Entropy provided interesting insight into the performances of these different analysis procedures. Based on strength of correlation between Multiscale Entropy and analysis result, we argued that this provided evidence of one analysis result being superior to the others.

We finally used Multiscale Entropy to provide a measure of optimal image compressibility. Using previous studies of ours, we had already available to us a set of images with the compression rates which were consistent with the best recoverability of astronomical properties. These astronomical properties were based on positional and intensity information, – astrometry and photometry. Papers cited contain details of these studies. Therefore we had optimal compression ratios, and for the corresponding images, we proceeded to measure the Multiscale Entropy. We found a very good correlation. We conclude that Multiscale Entropy provides a good measure of image or signal compressibility.

The breadth and depth of our applications lend credence to the claim that Multiscale Entropy is a good measure of image or signal content. The image data studied is typical not just of astronomy but other areas of the physical and medical sciences. Compared to previous work, we have built certain aspects of the semantics of such data into our analysis procedures. As we have shown, the outcome is a better ability to understand our data.

Could we go beyond this, and directly use Multiscale Entropy in the context of, for example, content-based image retrieval? Yes, clearly, if the user's query is for data meeting certain SNR (signal to noise ratio) requirements, or with certain evidence (which we can provide) of signal presence in very noisy data. For more general content-based querying, our work opens up any time allow greater recall, at the expense of precision. Our semantics-related Multiscale Entropy measure can be used for ranking any large recall set. Therefore it can be employed in an interactive image content-based query environment.

9 Total Information of Data Object and Channel

So far we have discussed the information content of large individual images. This has been based on multiresolution storage, which was motivated by the need for progressive transfer. In this section we discuss how this analysis can be extended to take into account not just storage, but also data transfer.

The vast quantities of visual data collected now and in the future present us with new problems and opportunities. Critical needs in our software systems include compression and progressive transmission, support for differential detail and user navigation in data spaces, and "thinwire" transmission and visualization. The technological infrastructure is one side of the picture.

Another side of this same picture, however, is that our human ability to interpret vast quantities of data is limited. A study by D. Williams, CERN, has quantified the maximum possible volume of data which can conceivably be interpreted at CERN. This points to another more fundamental justification for addressing the critical technical needs indicated above. This is that the related themes of selective summarization and prioritized transmission are increasingly becoming a key factor in human understanding of the real world, as mediated through our computing and networking base. We need to receive condensed, summarized data first, and we can be aided in our understanding of the data by having more detail added progressively. A hyperlinked and networked world makes this need for summarization more and more acute. We need to take resolution scale into account in our information and knowledge spaces. These are key aspects of progressive transmission.

Iconized and quick-look functionality imply greater reliance on, and access to, low resolution versions of image and other data. We have considerable expertise in the information content and hence compressibility of single images [14, 17]. But what is the compressibility of the total system, both storage and transfer, when many users avail of varying low resolution versions of the data? We are interested in ensemble averages over large image collections, many users, and many storage and transfer strategies. In other words, we are interested in the compressibility of, and information content of, single image files, and in addition the topology of search, feedback and access spaces.

Coding theory has traditionally been applied to single image files. An enhanced framework is provided by [3, 20]. The question is raised as to how progressively coded images are linked as separate files, and how the resolution and scale components are grouped in single files. A web layout, these authors point out, allows firstly and foremostly the logical cutting of one-dimensional objects, such as a large image, into pieces for individual downloading. Such cutting embodies some progressive multiresolution coding, i.e. summary information first. They look at various web design models which could be of interest in this context: simplified designs based on chain structures, tree structures, more general graph structures, and geometrical (or partition) structures.

We started with the use of resolution and scale in astronomy images, and it has led us to the consideration of optimal design of web sites! Zhu et al. [20] find that this problem of visual information management is typical of complex systems which are robust in design and have a certain tolerance to uncertainty. Access patterns show inherently bursty behavior at all levels, and therefore traditional Poisson models which get smoothed out in (temporal, access) aggregation are not applicable. A few conclusions for our purposes are as follows. Data aggregation, such as the use of the flux-preserving Haar wavelet transform discussed above, will provide no reduction in the information available. In turn this is bad news from the point of view of total efficiency of our image retrieval systems. Simply put, such data aggregation will the bad news, the good news is that data aggregation does not go hand in hand with destroying information. There is no theoretical reason why we should not avail of it in its proper context.

10 Conclusion

A selection of algorithmic, computational and encoding issues have been surveyed in this article. They are of particular relevance in the context of a range of important international projects which have started in the past few months. The "virtual observatory" in astronomy is premised on the fact that all usable astronomy data are digital. High performance information cross-correlation and fusion, and long-term availability of information, are required. The term "virtual" in this context means the use of reduced or processed online data.

A second trend with major implications is that of the Grid. The computational Grid is to provide an algorithmic and processing infrastructure for the scientific "collaboratories" of the future. The data Grid is to allow ready access to information from our tera and peta byte data stores. The information Grid is to provide active and dynamic retrieval of information, and not just pointers to where information might or might not exist.

The evolution of the way we do science, driven by these themes, is inextricably linked to the problems and often recently-developed algorithmic solutions surveyed in this article.

As just one address for further information on innovative developments is this broad area we give the following: iAstro, "Computational and Information Infrastructure in the Astronomical DataGrid", http://www.iAstro.org. This is a 4-year (from late 2001) European collaborative project.

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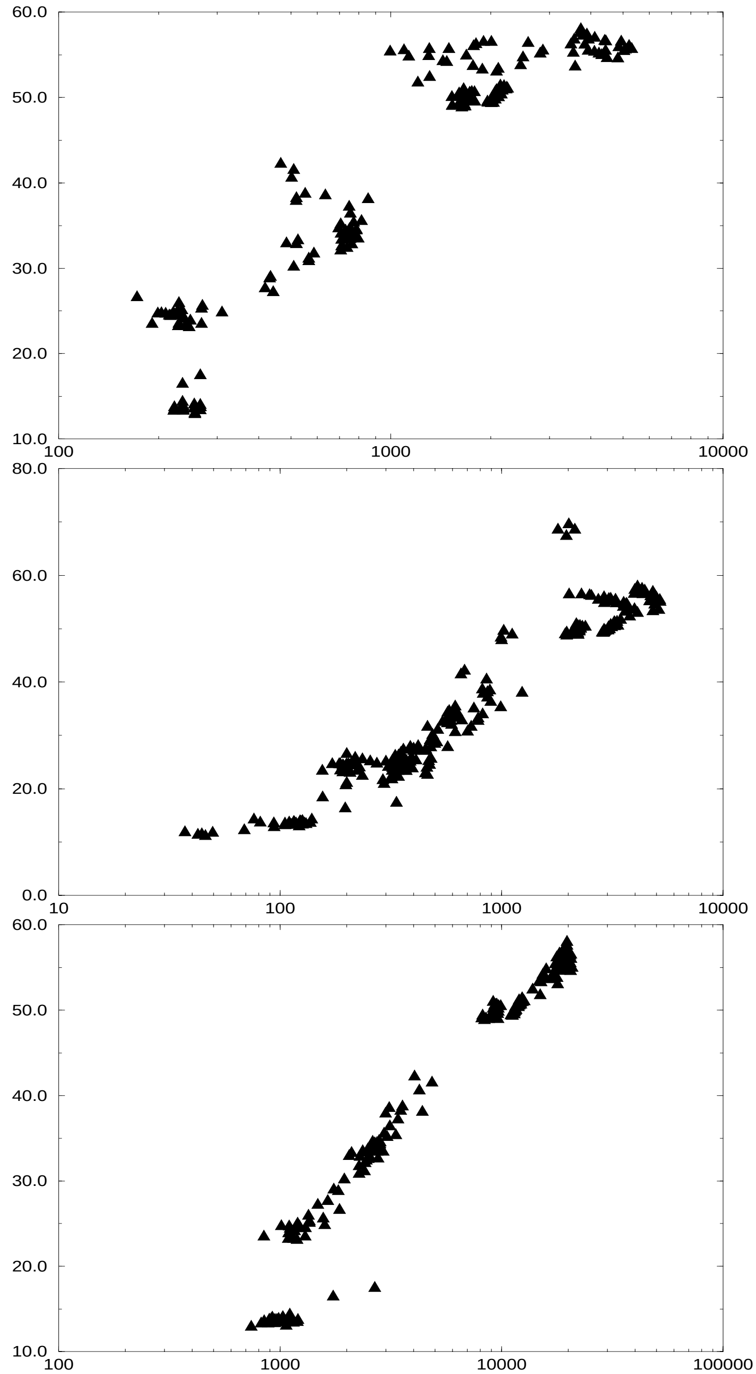

Figure 5: Multiscale entropy versus the number of objects: the number of objects is, respectively, obtained from (top) the USNO catalog, (middle) the Sextractor package, and (bottom) the MR/1 package.

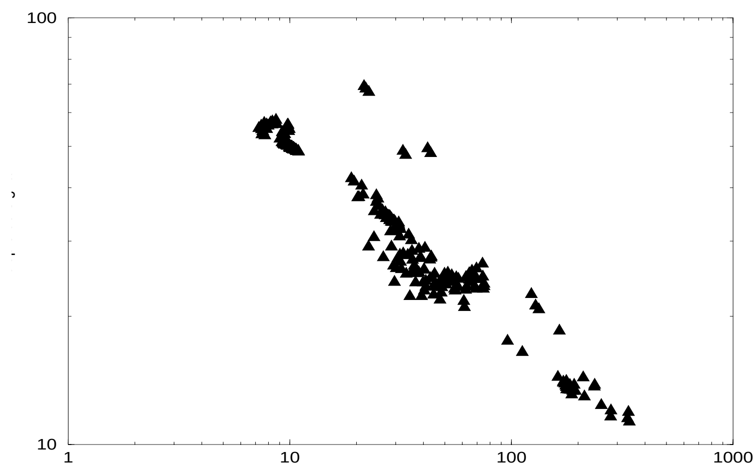

Figure 6: Multiscale entropy of astronomical images versus the optimal compression ratio. Images which contain a high number of sources have a small ratio and a high multiscale entropy value. With logarithmic numbers of sources, the relation is almost linear.