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Advanced image processing in radiology

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It is clear that radiology is in the process of making a transition between "analogue" imaging and digital imaging. While this has the benefit of enabling electronic retrieval, archiving etc. (the picture archiving and communications system field which is covered elsewhere in this issue), the data are also available for use in so-called advanced image processing. However, the aim of image processing should not be just to produce prettier pictures, but to extract good clinical information, and a legitimate question is — is advanced image processing in radiology required? However, advanced processing methods need to incorporate clinical knowledge and be defined using clinical constraints. The continuing advances in hardware performance have made many previously computationally unattractive methods feasible, an example being iterative reconstruction in tomography, which is now routine in nuclear medicine, but not CT. Both linear and non-linear operations can be considered, including the important topic of model fitting, where two classes of method are important: data driven and hypothesis driven. Examples of data driven methods are principal component analysis, factor analysis and independent component analysis, where the model is derived from the data. Hypothesis driven methods are all implicitly or explicitly based on model fitting; a preliminary data driven step followed by hypothesis driven approaches which could be called constrained statistical image analysis. Examples are shown as used in nuclear medicine and MRI. Another important problem in radiology is that of multimodality image registration and fusion. In the analysis of such data, tests against reference data sets (atlases) are required, normally requiring warping the data sets in space, for example by the use of optic flow, or some kind of diffusion equation. Real-time analysis of data during acquisition can lead to optimization of acquisition procedures, which is an example of intelligent image acquisition. Incorporation of such image analysis techniques into a decision support system is highly desirable. The availability of distributed image processing and data, usually called "grid" computing, is likely to significantly change the types of methods used and their availability.

Summary

- Radiology is in the process of making a transition between "analogue" imaging and digital imaging and between two-dimensional and three-dimenstional imaging.
- Advanced processing methods need to incorporate clinical knowledge and be defined using clinical constraints.
- Two classes of method are important: data driven and hypothesis driven.
- In the analysis of such data, tests against reference data sets (atlases) are required.
- The availability of distributed image processing and data, usually called "grid" computing, is likely to significantly change the types of methods used and their availability.

The advances in computer hardware over the last decade are remarkable. We can note a gain in speed of conventional personal computers of about a factor of 20 over the last 3 years. The progress seems to be continuing into the future. This gain in performance has made possible many new methods, which previously could not be contemplated at least in routine, now practical. One change which can already clearly be observed is the change from two-dimensional (2D) imaging (for example of CT slices) to 3D acquisition and volume display, as a result of the impact of spiral CT scanners (and advances in MRI and ultrasound). However, this improvement in performance has been accompanied by, or has resulted in, a considerable increase in the quantity of data available, a good example being from single cardiac transaxial slices to gated 3D acquisitions in MR and ultrasound and CT. However, a key requirement is not just to do something faster, but to perform a task that will enhance the value of the results.

One specific issue has been with respect to the use of parallel processing computers, as opposed to conventional serial machines, where progress in the latter has made the use of the former redundant. Indeed, it has been suggested that for certain very large problems, it might be better to wait for the improvement of speed of hardware in order to complete the task faster than tackling it straight away on current slower hardware! Of course the improvement in hardware has also been accompanied by an increase in the overhead used by operating systems and certain well known packages where no perceptible gain in performance is obvious to the end user. However, this limitation does not normally apply to image processing tasks required in radiology, which are much more computer intensive than for example a word processor, and real gains can be achieved.

A second issue has been the incorporation of smart processing as part of the (intelligent) acquisition stage of various devices, incorporating microchips, such as DSP processors within the signal processing components of the detectors. It has as a result been difficult to distinguish pure acquisition from pre-processing, and to provide a clean interface between acquisition and processing.

Advances in conventional image processing and image reconstruction

Having acquired good data, we need to do something with them. Conventional image processing includes such operations as noise reduction, segmentation and region identification, and image display. Transforms and filters form very basic image processing tools (see for example [1]). Essentially one chooses an appropriate set of basis function (for example sinusoids), a transform (for example Fourier) and then one filters the "eigenvalues". Filtering is just the process of reconstituting the modified version of the original data as being a weighted set (the filter) of the eigenvalues multiplied by their corresponding basis functions. While this is well understood in the Fourier frequency domain, such operations may be generalized by choosing other basis functions, for example as in the Karuhen–Loeve transform. In addition the process may include constraining the filtering process by methods which may be called regularization. The aim of the filtering process is normally to alter the properties of the image, for example the noise characteristics. Such a filtering operation is linear, but non-linear methods such as anisotropic blurring are also of considerable interest. An example of considerable interest, for example for detecting change, is that of Kalman filtering [2, 3].

Tomographic reconstruction is an example of the solution of an inverse problem, which is another basic tools in image processing [4]. Here the key feature is to set up a good forward model relating any set of solutions; in CT the attenuation map (electron density distribution) **A** in the patient or object, and the observations **O** that these would generate. This may be expressed in matrix notation

$$\mathbf{O} = \mathbf{F}\,\mathbf{A}$$

where **O** and **A** are normally given in vectorized form and **F** is termed the forward model or operator. The problem is then to choose a good method for solving this rather large set of simultaneous equations. At present the most common method of performing this task in CT is by filtered backprojection, but an iterative method such as maximum likelihood expectation maximization (MLEM) or ordered subset expectation maximization (OSEM) should be a considerable improvement using an equation of form:

$$a_j^{n+1} = a_j^n \sum_i f_{ji} \left[\sum_k f_{ki} a_k^n \Big/ o_i \right]$$

where n is the nth iteration, a_j is the jth element of the guessed solution **A**, f_{lm} is an element of the forward operator and o_i is the ith element of the observations **O**. In reality, this operation is relatively easy to understand. An iterative approach is used where a^n is the current guessed image. The expression between the square brackets is just the ratio of the prediction of what the observed data would have looked like, coming from this guessed image (that is the forward "projected" guesses) divided by the real observed data. If this ratio is one, then the guess fits the observation. However, this ratio of observations needs to be converted to corrections for the pixels in the image, which is performed by the term preceding the square brackets. The resulting value is then used to modify the current guess at the corresponding pixel. This continues until we find some good reason to stop (which is not as easy as it sounds). Two standard methods are used: MLEM and OSEM, where the advantage of the latter is faster convergence. Both methods are considerably better in terms of signal to noise ratio and the reduction of artefacts than conventional filtered backprojection, but are at least an order slower. However, progress in computing (Moore's law) suggests that this should not remain a problem for very much longer. However the dramatic increase in volume of data resulting from, for example, spiral CT goes in the other direction. Spiral CT data also require some additional refinements to produce high quality isotropic data, in particular when working with images after contrast medium injection.

Another mathematical technique called regularization can be used to impose additional constraints to the solution and can be very helpful [5]. A typical form of regularization is to minimize not just the fit, *i.e.* the distance, between observations **O** and the corresponding solution values generated, which were generated from the guessed solution (**A**) by applying the forward model (**F**), but also, at the same time, minimizing some property of the reconstructed image or solution, for example its smoothness. This is normally obtained by applying a regularizing operator (**R**) to that solution, for example an estimate of smoothness. A common form for the operator **R**[] is to look at a derivative, for example the first or second. Thus we find the best solution in the least squares sense which is also the smoothest, for example. Regularized reconstruction can be of help where noise levels are high, for example in nuclear medicine, but also where data are undersampled, for example cardiac MRI. Computing time–activity curves or uptake rates for contrast medium in CT and MRI can be performed more accurately indirectly by use of the original raw projection data, rather than by defining a region of interest on the reconstructed data and deriving the time curve directly from the reconstructed sequence. This has particular interest in non-linear (model based) imaging applications such as electrical impedence tomography, optical tomography and even attenuation correction in nuclear medicine.

Image processing and the imaging chain

Image processing occupies only one part of the imaging chain, as illustrated in Figure 1. The imaging chain starts with acquisition and preprocessing to make good clean data available. Image processing as such is a precursor to the stage of image interpretation and decision making. This process has to be integrated within a system of validation and evaluation. Finally other data than images need to be integrated.

Thus the aims as such of image processing can be described as firstly detection, secondly measurement and hence, finally, description. While the problems of detection have often dominated the area of medical image processing, the problems of image interpretation are in the process of becoming considerably more important. This may be illustrated by some examples. One such example is in the handling of lung/liver CT scans looking for small lesions, or, in nuclear medicine, sentinel node images. Small lesions and sentinel nodes may be detected by some kind of matched filter, giving the probability a particular feature has of being the object we are trying to detect. It should be noted that information other than intensity variations may be of value, for example texture. It is well known that the human eye is rather insensitive to variations in texture, and additional information may be obtained by detecting changes in other features of the image than grey scale intensity; an example applied to nodule detection and characterization in CT images is indicated in Figure 2. The second stage is that of measurement: of what size, where in the structured object are they found, perhaps also looking at their shape and texture. This leads an attempt to determine a description: benign/malignant. The improvement of signal to noise ratio requires a filter, which as previously indicated implies a constraint and a model. The derived description is itself a model. A second example is that of tumour staging, where initially we have the problem of finding the tumour, then measuring its volume and invasion and perhaps change in size with time, finally that of classification, determining its "stage" from which a diagnostic strategy can be planned. Follow up of tumours, in particular of therapy, also requires quantitation.

The integration of image processing, for example within a decision support system, requires forward and backwards inference in the process of evaluation to what may be called a goal (the clinical decision). Goals can be divided into sub-goals and indeed exclusions ("this" information is incompatible with "that" statement). A knowledge hierarchy exists, going from high level such as the clinical condition, to intermediate knowledge such as the description of organs or tumours, down to low level knowledge such as that associated with blood vessel…. This topic is still the subject of active research. Thus while conventional image processing is often about enhancing edges and performing operations on pixels or voxels, advanced

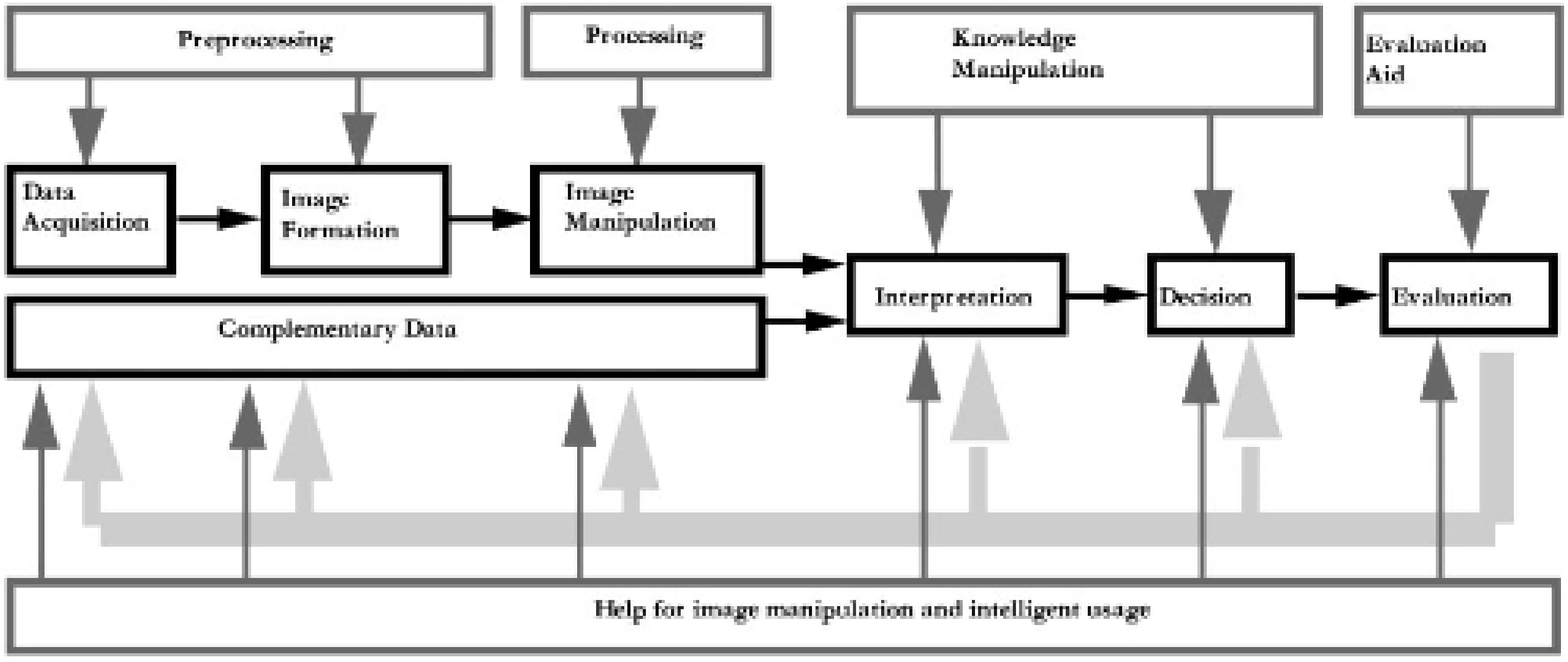

Figure 1. The imaging chain from acquisition to evaluation.