Managing complex processing of medical image sequences by program supervision techniques

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ABSTRACT

Our objective is to offer clinicians wider access to evolving medical image processing (MIP) techniques, crucial to improve assessment and quantification of physiological processes, but difficult to handle for non-specialists in MIP. Based on artificial intelligence techniques, our approach consists in the development of a *knowledge-based program supervision system*, automating the *management* of MIP *libraries*. It comprises a library of programs, a knowledge base capturing the expertise about programs and data and a supervision engine. It selects, organises and executes the appropriate MIP programs given a goal to achieve and a data set, with dynamic feedback based on the results obtained. It also advises users in the development of new procedures chaining MIP programs. We have experimented the approach for an application of Factor Analysis of Medical Image Sequences as a means of predicting the response of osteosarcoma to chemotherapy, with both MRI and NM dynamic image sequences. As a result our program supervision system frees clinical end-users from performing tasks outside their competence, permitting them to concentrate on clinical issues. Therefore our approach enables a better exploitation of possibilities offered by MIP and higher quality results, both in terms of robustness and reliability.

Keywords: artificial intelligence, knowledge-based system, medical image processing, multidimensional image analysis, program supervision.

1 INTRODUCTION

The medical imaging environment deals with multi-modality images, multi-dimensional data, imprecise information and involves image manipulation tasks according to both clinical and methodological goals. This environment is open and evolutive, even more with the development of functional medical imaging. Functional imaging provides robust quantification of parameters and helps identifying physiological, mechanical, metabolic models underlying the observed phenomenon (e.g. brain or heart perfusion[1] , cardiac wall movement[2]).

While qualitative information may be obtained by simple visual inspection of these images, quantitative information is the result of image processing. However, medical image processing (MIP) methods used in clinical practice

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are usually either very simple or very dedicated. An increasing number of more complex and performing methods are developed in research laboratories. Although a wider access to these evolving MIP techniques is crucial to improve assessment and quantification of the studied processes, these are not widely spread in clinical practice.

Typically, MIP involves two kinds of users. A first category of MIP users are *clinical researchers*, who elaborate clinical protocols including MIP procedures (i.e. a suitable combination of MIP programs) to be safely used in clinical context. Their kind of expertise is both pragmatic and clinical. The second category are *clinical end-users*, who use MIP procedures provided by clinical research in every-day practice. As their concern is only medical, they find it difficult to handle these procedures without the specialised knowledge required (computer science, statistics, physics, etc.), for which they are not always competent.

Thus the technical complexity of MIP stresses the need for an interface ensuring knowledge transfer to clinical users. Clinical researchers need a system that helps them explore the possibilities of a MIP technique with respect to new clinical goals, without any need of knowing programs algorithmic details. Clinical end-users need a system that helps them to use MIP procedures and which they can rely on to focus on diagnostic or therapeutic tasks.

Our aim is to improve the performance of clinical users by efficient use of (functional) MIP. Based on artificial intelligence techniques, our approach consists in the development of a *knowledge-based program supervision system*. Such a system aims at automating the *management* of MIP *libraries*, freeing users from manually performing tasks outside their scope. It offers a good compromise between automation and interaction in the use of these libraries by providing the specialised knowledge that may be required.

Acting as a knowledge and know-how repository, a program supervision system captures in a formal manner both clinical researchers' and medical image processing specialists' knowledge about the use of MIP programs. It uses this knowledge to select, organise and execute the appropriate programs in the library given a goal to achieve (e.g. to estimate spatial localisation and temporal behaviour of physiological processes) and a data set (e.g. dynamic MRI), with dynamic feedback based on the results obtained. Such a system also advises users in the development of new procedures.

It is important to mention that our purpose is not to replace end-users in tasks for which their medical knowledge and interpretation skills are required. Program supervision is in that way different from automatic image interpretation, which aim is to automate part of the diagnostic reasoning[3–5] .

The approach we propose is based on our previous work in program supervision applied to image processing in different domains[6–8] and in particular in MIP[9,10] . This paper is organised as follows: next section identifies what class of problems is concerned with program supervision and justifies the need for it; third section explains the technique of program supervision; fourth section illustrates program supervision applied to a representative example: the Factor Analysis of Medical Image Sequences (FAMIS) library[11,12] ; finally, fifth section discusses results before concluding.

2 RATIONALE

The great variety of medical examinations (e.g. organs, pathologies) implies the acquisition of many different types and modalities of medical images. They are related to clinical goals, both specific (e.g. "chemotherapy follow-up", "myocardic perfusion") and general (e.g. "physiological functions estimation"), that can be solved by the use of MIP. The simple analysis methods often employed, such as the use of regions of interest, do not take into account the complexity of the medical imaging environment, so are neither robust, nor reproducible. This is why more performing "complex" methods are proposed by methodological research laboratories, especially in the field of functional medical imaging. However, increasing complexity in MIP techniques makes them more and more difficult to handle by non-specialist users. The choice of the appropriate MIP programs, the planning of their execution and the evaluation of their results involves both methodological and clinical knowledge, in addition to knowledge relating these two.

The combination of these different kinds of knowledge leads to the definition of MIP procedures, chaining programs, based on information about the case to study (e.g. acquisition modality, contrast medium, type of examination) and the clinical goal to reach.

Indeed, new MIP techniques need first to be explored at a research level, in order to define their best possible exploitation, as part of global therapeutic, diagnostic or interventional protocols. The role of clinical researchers is thus to elaborate MIP procedures for every-day practice, adapted to (new) clinical goals. At the moment, clinical researchers often need assistance from methodologists, who possess the expertise about the use of the programs and are competent for technical and algorithmic details about the programs. Methodologists know what programs are available, how they should be used, what possible choices are, how they can be made, what are the consequences of different choices. In order to focus on clinical issues, clinical researchers should be freed from the management of this specific methodological knowledge, thanks to a system providing them with a clear view over the MIP program library as a set of black boxes. The efficiency of clinical researchers would be increased with a system including facilities to explore MIP possibilities in a more or less systematic way, e.g. trying every possible solution.

Similarly, clinical end-users need some system relieving them from the management of MIP programs: selecting, scheduling and executing the MIP appropriate procedures to solve their problem; presenting results so they can interpret them; finding alternative solutions when results are not satisfying. Such system must be flexible enough to adapt general strategic knowledge defined by experts to real cases. It therefore must be based on well formalised knowledge, easy to modify and to extend. Finally, such a system must solicit end-users only with respect to issues they are concerned with: problem definition and clinical results interpretation.

Tools that enable complex processing and hide implementation details from the user were developed early in the process of automatic medical image processing. For example, the system CL/ONE[13] was developed in the late 70's, and later commercialised for medical image processing in nuclear medicine, enabling the reuse of programs and applications in different contexts. It already addressed issues related to interactivity and visualisation. But knowledge description was not sufficiently developed and no intelligent planning mechanisms was included.

Existing (medical) image processing toolboxes (e.g. 3DViewnix[14] , Khoros[15] , AVS, IDL) are "surface systems" mainly focused on "look and feel" issues, as they only provide users with a syntactic description of functions available and means of information presentation. Indeed, they require from the users to have considerable competence in image processing, to be able to combine functions in a procedure. Current commercial medical imaging devices also provide rather limited facilities in the handling of predefined image processing procedures. None of these systems takes in charge choice, tuning or chaining of programs to fulfil a given goal.

To meet this need, (knowledge-based) program supervision systems have appeared, as a result of both the development of MIP program libraries and of artificial intelligence techniques. They capture both the methodological knowledge about the programs (e.g. processing compatibilities, presentation guidelines) and the clinical knowledge (e.g. specificities of the physiological area observed). Unlike shell scripts of instructions, such systems provide flexibility, dynamic adaptation facilities and extension possibilities (i.e. easy addition of new procedures), necessary to face the rapidly changing medical environment. They offer a lisible, multiple view on a MIP library, related to the different clinical purposes it can be used for. This way they support many more to help users who do not have specialists' image processing knowledge.

In the past few years, several intelligent systems have been developed for specific application domains, as well as for more general purposes [16,17] . All these systems propose a more or less fine description of data and programs, used by a supervision engine. They differ by the reasoning mechanisms (e.g. planning strategy) they provide to perform program supervision. In the medical imaging domain, we can cite: VISIPLAN[18] , which is an interactive object centered planner for biomedical image analysis; BORG[19] , which has been tested for segmentation of cytological images; IAMI[20] , which is also a tentative program supervisor especially developed for pulmonary examination in nuclear medicine; IQSS[21] , that mainly focuses on the knowledge representation for program supervision; etc.[22] . Several more general purpose systems in program supervision exist, like MVP[23] , VSDE[24] and OCAPI[6] .

Our approach of program supervision is based on previous work in our teams, especially with the OCAPI system[6] .

Given the specification of a knowledge base for specific data and program library, OCAPI can generate a dedicated knowledge-based program supervision system. OCAPI provides a hierarchical skeleton-based planner using simple data descriptions. It is based on the frame formalism to represent concepts as goals, operators, or plan schemes and production rules to represent the different criteria which are associated to these concepts (e.g. for choice, parameter initialisation, intermediate results evaluation).

3 PROGRAM SUPERVISION TECHNIQUE

Program supervision consists in the automation of the management of a program library, helping users to choose, order and apply programs to perform a certain task. This section explains the knowledge-based program supervision technique that we propose as well as its adaptation to MIP supervision specific needs.

3.1 Principles of program supervision

A program supervision system comprises[25] : (1) a library of executable programs; (2) a knowledge base capturing the expertise about the use of programs and data, provided by experts who have specialised (methodological or clinical) knowledge; (3) a supervision engine respecting the different phases of the experts' reasoning process.

The supervision engine that we propose performs four reasoning phases (see figure 1). An initial *planning phase* determines the best strategy to reach the goal of the end-user. The result is a partial plan which combines programs, considered as black boxes (step 1). An *execution phase* then launches the individual programs in the plan. During this execution phase the system can dialogue with the procedures and initialise necessary parameters (either using initialisation expert knowledge or in collaboration with the end-user) (step 2). An evaluation phase assesses the quality and contents of the resulting data at the end of each executed program, with respect to what was foreseen. This evaluation can be performed by different (non-exclusive) means: using expert knowledge, by the end-user, by comparison with predefined expectations, etc. (step 3). If results are correct, planning can continue (step 4). If results are judged incorrect (step 5), a repair phase decides what following action to undertake, depending on the evaluation judgements. The repair action can either be to modify the plan (step 6) or to re-execute the "guilty" procedure with different parameters (step 7).

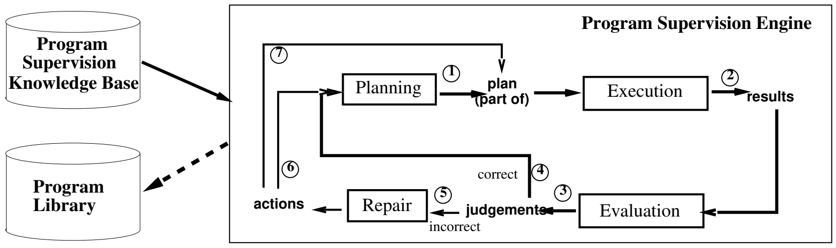

Figure 1: *Architecture of a program supervision system and principal reasoning phases of the engine, explained in the text.*

Planning and execution are usually interleaved because the exact form of the plan typically depends on information that is only available at execution time. Since environment description is incomplete, thus programs effects cannot be completely foreseen, the supervision engine executes the programs in a reactive fashion, including result monitoring, fault diagnosis, and repair[26] . Different planning strategies can be chosen, that organise selection, ordering and execution tasks differently with respect to their appropriateness to model experts' reasoning. Hierarchical planning is prefered in program supervision, mainly because the expert often thinks in terms of abstract plan schemes. A hierarchical planner first constructs an abstract plan, then refines it for a particular situation, based on actual data.

3.2 Medical imaging specific needs in program supervision

In order to build a supervision system for complex medical imaging, the specific aspects associated with the medical imaging environment must be identified and modeled in terms of images and goals, processing available and user requirements. Indeed, the medical image processing context[27,28] : 1) is multi-modality; 2) is multi-dimensional, requiring specific n-D programs to take into account the relationships between images inside image sequences; 3) deals with much imprecise and incomplete information and image manipulation goals that can be both methodological and clinical; 4) is open and evolving and cannot contain exhaustive definitions of clinical applications; is unbounded (unforeseen exceptional cases can occur); 5) critically depends on the way information is presented to the user.

By observing MIP experts' reasoning process, we have identified the need for a mixed kind of supervision: hierarchical at a high level of abstraction and dynamic at a finer level. Indeed, the whole process cannot be foreseen, as a result of the non-exhaustive aspects of both the clinical objectives and the data to process. In addition, complete automation of procedures is not considered desirable in the MIP environment. If needed, user's competent help can be required by the system, for instance for visual evaluation of intermediate results. We have enriched our program supervision model so it can manage the complexity of both data and reasoning in MIP, automate only uninteresting tasks and react to the specific case to study.

Based on the description of data and operators together with their criteria, the proposed supervision engine reasons thus as follows[29] . Planning is guided by predefined high-level skeletons of major actions to execute for a given goal. This enables to plan coarse steps in a global way with respect to image data, without any information about executable programs. Execution is reactive: it dynamically adapts the partial plan to real conditions, driven by concrete data and execution constraints, verifying type compatibility between actual data and data that the selected operator can process. Evaluation is either automated thanks to experts' criteria for methodological results, or more interactive, for steps needing users' specific knowledge. This phase integrates an adequate way of presenting results, with respect to user's knowledge level. Finally, repair mechanisms can backtrack to delicate steps or try alternative solutions.

The reactive aspect of the supervision engine enables to dynamically adapt the main strategic skeleton of data transformations by adding secondary or alternative processing if data do not satisfy main processing constraints. Knowledge about secondary processing is part of the expertise about the use of programs that need them, so it must be included to the description of the programs (e.g. as pre-conditions such as "input data with no movement noise"). The supervision engine then is able to base the planning on the satisfaction of operators applicability constraints. Besides, based on goal and data, high-level strategic knowledge guides main processing. Examples are the knowledge that processing has to be repeated on each part of a symmetric organ (e.g. knees or brain), and results compared to each other; or that processing is multi-scale, progressively focusing on the interesting area.

3.3 The knowledge base

The different types of knowledge, such as data, programs and criteria are described in a knowledge base, structured by different knowledge concepts. The program supervision engine uses the information they contain to build a solution to a given goal. The efficiency of the supervision engine is tuned by what kind of knowledge is available in the knowledge base. Together with their specific adaptation to MIP program supervision needs, here are exposed the knowledge concepts included in a knowledge base.

To begin with, data are described within *data types* in a clear and structured way to allow a program supervisor to take necessary decisions. The richness of the data involved implies that MIP is essentially data-driven. Therefore the contents of data must be modeled together with their impact on the reasoning process[28] . The data are sequences of images that contain information both about acquisition conditions and observed objects. For example, data acquisition information (e.g. the acquisition modality), fixed once and for all, together with data contents information (e.g. information about the elements that are present in the image such as hemodynamic characteristics), is used in the global planning, where the successive transformations of the data are described. Data presentation information (e.g. visualisation parameters) enables adapting the plan in reaction to real execution parameters. Finally, data implementation (e.g. the way the image is structured, its physical location) is needed when data is accessed to.

As experts often think about processing in terms of abstraction levels, the knowledge concepts that we have defined to describe programs for supervision easily fit into a hierarchical construction of the knowledge base. Associated to the hierarchy, a *goal* describes, by means of constraints, the suitable properties that must hold in a state of the world to decide that a certain objective is achieved. Together with a set of data, it enables the definition of the user's *initial request*.

Operators describe programs as well as the information needed to apply them in different specific situations[30] . They include knowledge such as: functionality (e.g. estimation of brain perfusion or of mechanical characteristics of the cardiac wall), input and output arguments (e.g. temporal sequence of images), parameters (e.g. size of region of interest), characteristics (e.g. speed or memory consumption), preconditions (e.g. no patient movement in the sequence) and effects (e.g. output data contain spatial localisation of a physiological process and its temporal behaviour, like the peri-tumoral vascularisation of an osteosarcoma), etc. Various criteria are attached to operator description, e.g. how to initialise and adjust parameter values before their application (*initialisation criteria*, *adjustment criteria*), how to evaluate output arguments after application (*assessment criteria*), how to react in case of bad results (*repair criteria*). These criteria often are production rules.

We distinguish two kinds of operators. *Terminal operators* describe executable programs by including a reference to actual programs of the library and how to activate them. *Complex operators* describe procedures as predefined partial skeletons of plans also named plan schemes. They correspond to networks of possible connections between operators (e.g. choice, sequence, iteration), in order to achieve a given goal. Complex operators contain information about data flow between their elements, together with tactical knowledge i.e. criteria to decide how to cross the network (*choice criteria, applicability criteria*). Different plan schemes can be associated with the same set of programs.

4 EXAMPLE: UTILISATION OF FAMIS

We have experimented our program supervision approach by developing a program supervision knowledge base for Factor Analysis of Medical Image Sequences (FAMIS)[11,12] programs.

4.1 The FAMIS knowledge base

FAMIS is a typical example of functional MIP complexity and slow diffusion. The performing statistical methods it is based on are difficult to understand by non-specialists. These methods are delicate to use, as the parameters they involve have much influence on their behaviour and on the interpretation of their results. FAMIS can be used for a family of applications, including various types of data and clinical goals. For instance, dynamic MRI or NM image sequences are analysed with FAMIS to get a spatio-temporal estimation of the underlying physiological functions (methodological goal), in order to characterise a tumoral area (clinical goal). Moreover, FAMIS can be included in larger medical protocols, like e.g. therapy follow-up that involves the comparison of different analysis results.

The larger use of FAMIS implies a necessary task of procedure elaboration, to transfer strategic clinical knowledge about its utilisation. To solve a new clinical goal by analysing new image sequences (e.g. dynamic MRI mammograms), FAMIS utilisation needs tuning based on both methodological and clinical knowledge. Indeed, it can be very delicate to determine the adequate data to analyse, i.e. what characteristics of the image sequence are appropriate (e.g. pre-injection image subtraction when a contrast medium has been used for acquisition), what area is both of interest to analyse (e.g. slices that contain the tumor) and respecting FAMIS prerequisites (e.g. no movement during sequence), if a mask is needed (e.g. to hide an area that takes in all the contrast). Knowledge like the kind of thresholding method to use, with respect to the physiological structure to analyse (e.g. if the geometricity of the organ to analyse is irregular, like kidney, statistical thresholding is preferable) or the number of functions to look for also involves both methodological and clinical skills. Furthermore, the result assessment, based on e.g. the shape of factor curves and the way they can be related to a clinical significance is most difficult.

FAMIS method great lines are well defined and unlikely to change much from one execution to another. It can therefore be coarsly decomposed in six major steps. *Data preparation* is a preliminary step that performs some pre-processing on data before major processing. Then *segmentation* focuses the further analysis on the pertinent signal. *Orthogonal analysis* reduces this information to its noisiless expression. Next, *oblique rotation* closely approximates the physiological functions under domain constraints, like necessary positivity of the solutions, for example. *Factor and image computation* then processes the physiological factors and their spatial distribution. Finally *result presentation* performs visualisation tasks, as well as results postprocessing if needed. Beside these six fixed steps, possible secondary processing steps can dynamically be added, with respect to specific adaptation of FAMIS to the case to solve. Examples are patient's movement correction before segmentation or comparison of the results of FAMIS on pathological and corresponding healthy parts of an organ at the end of both processing.

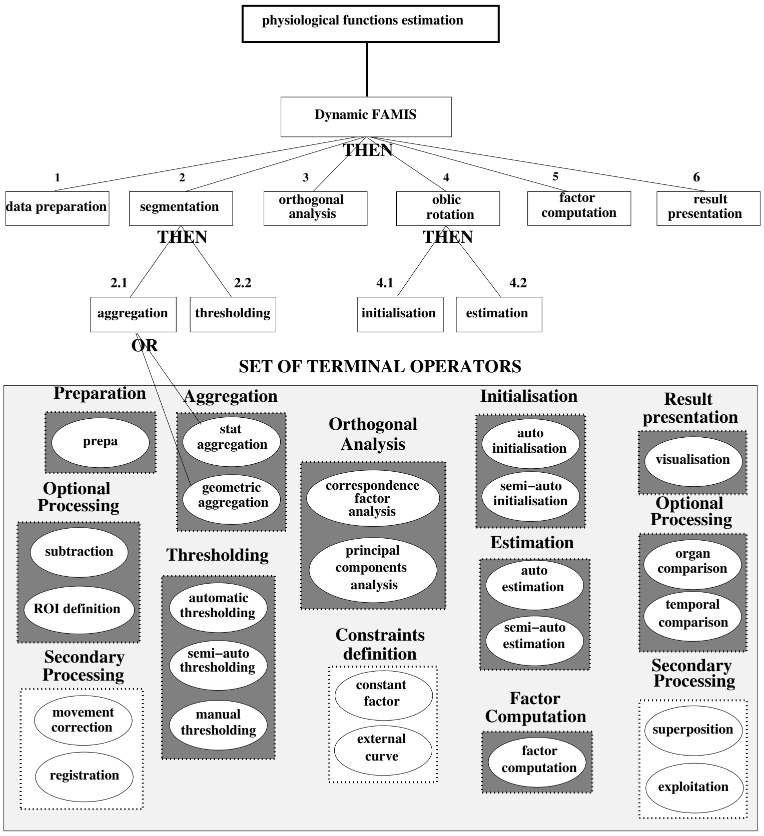

Figure 2: *Main tree of complex operators involved in the FAMIS knowldegde base and set of terminal operators. Terminal operators on grey background correspond to either alternatives of main processing steps or to optional processing, terminal operators on white background are secondary processing.*

The FAMIS knowledge base is organised with respect to a hierarchical viewpoint on the main processing steps in addition to a non-ordered set of terminal operators grouped by the functionality they achieve (see figure 2). The higher abstraction level is a complex operator that chains 6 main operators in a sequence, each associated to one of the step identified: data preparation, segmentation, orthogonal analysis, oblique analysis, factor and image computation, result presentation. Each operator either is decomposed into a sequence of functionalities to achieve or corresponds to a group of possible operators among which a choice must be made (e.g. aggregation step). Some steps can be optional, with respect to applicability criteria that test data characteristics at execution (e.g. subtraction). The basic abstraction level comprises terminal operators, some linked to the executable FAMIS programs (e.g. geometric aggregation, statistical thresholding), others as secondary processing executable programs (e.g. movement correction) or optional processing.

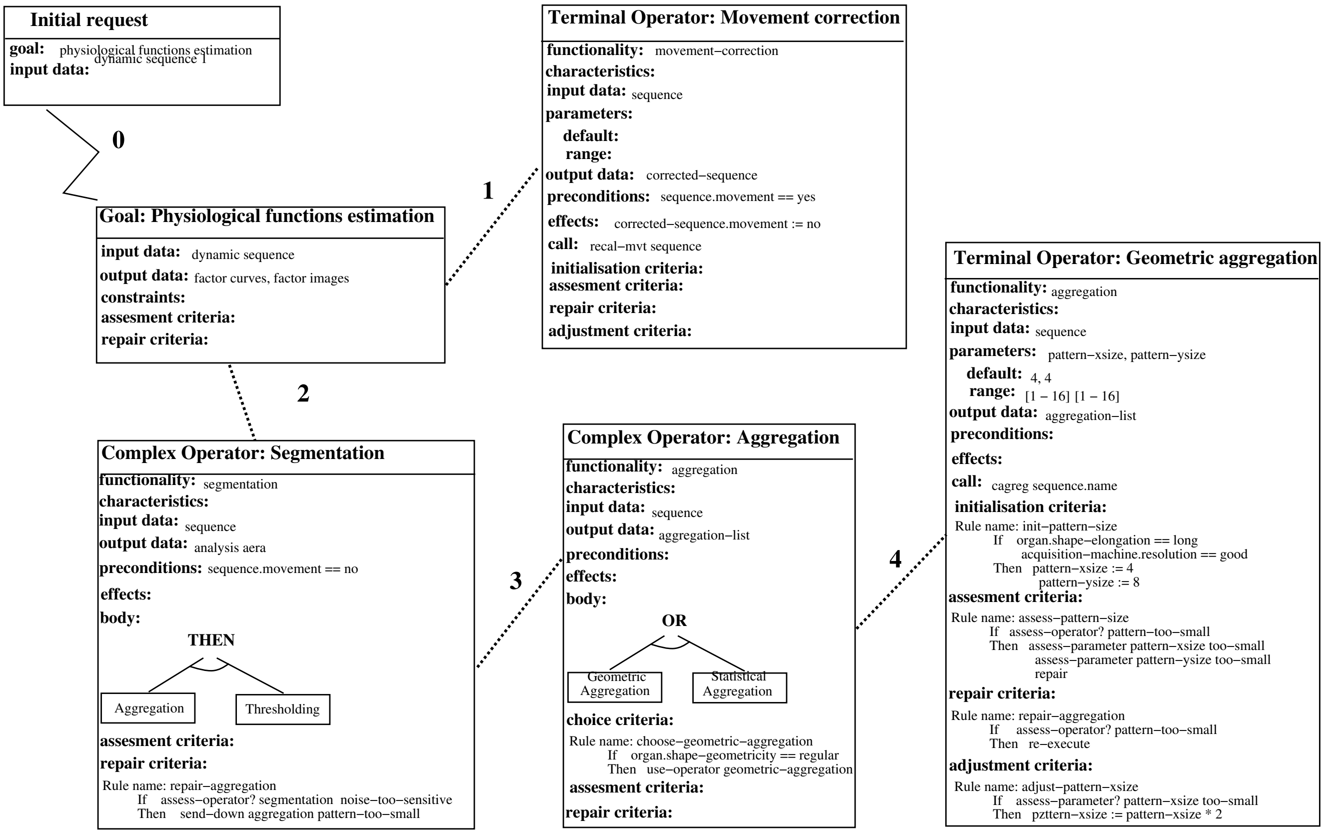

Figure 3: *Example of main knowledge concepts in the FAMIS knowledge base. (0) Initial request defines the goal to achieve on a given set of data. (1) The resolution of goal "physiological functions estimation" involves complex operator segmentation, which preconditions are that input sequence does not contain movement. As effects of terminal operator movement correction are that output sequence has no movement, this step can be added dynamically if the analysed sequence contains movement. (2) Complex operator segmentation can then be executed. (3) It begins with a step solved by complex operator aggregation, on its turn solved either by terminal operator geometric aggregation or by terminal operator statistical aggregation. A choice criteria enables to decide between both solutions based on input sequence or contextual information characteristics. (4) Then, for example, terminal operator geometric aggregation is executed. Just before execution, its parameters are initialised thanks to initialisation criteria or default values specification. When it comes to assessment and repair of segmentation, a combination of assessment, repair and parameter adjustment criteria are used to decide what action to undertake.*

Figure 3 is an illustration of the knowledge that can be found in the FAMIS knowledge base, focused on the segmentation step. Some image sequence characteristics that determine the exact processing for segmentation are e.g. the presence of noise, the resolution of the acquisition machine, the geometricity of the observed organ shape, the use of a contrast medium for acquisition, etc.

4.2 Application to the follow-up of osteosarcoma chemotherapy

This prototype has been tested on a well defined clinical research protocol, using FAMIS as a means of predicting the response of osteosarcoma to chemotherapy, with both MRI and NM dynamic image sequences[31,32,10] . It consists in comparing FAMIS results at different moments during chemotherapy, to observe tumor evolution. Figures 4 and 5 show the kind of results FAMIS can produce for this application.

To meet this application specific needs, we have integrated applicative strategic knowledge related to this clinical goal. High level strategic criteria are based on the contents of data such as the observed organ, related to sequence acquisition process (i.e. NM or MRI). In particular, organ parity, its shape, its vascularisation level are important. Osteosarcoma images often concern knees or tibia regions, which are double elongated organs. Often, one part of organ is tumoral whereas the other is healthy. Furthermore, knee is much vascularised by femoral arteria, whereas tibia is not. The parity of these organs induce several procedures represented in the knowledge base by complex operators in which FAMIS is seen as a sub step. For instance, when both knees are on images (as in NM), FAMIS can be applied first to healthy knee so as to have reference results, then to tumoral knee. A results comparison step is then added at the end of procedure.

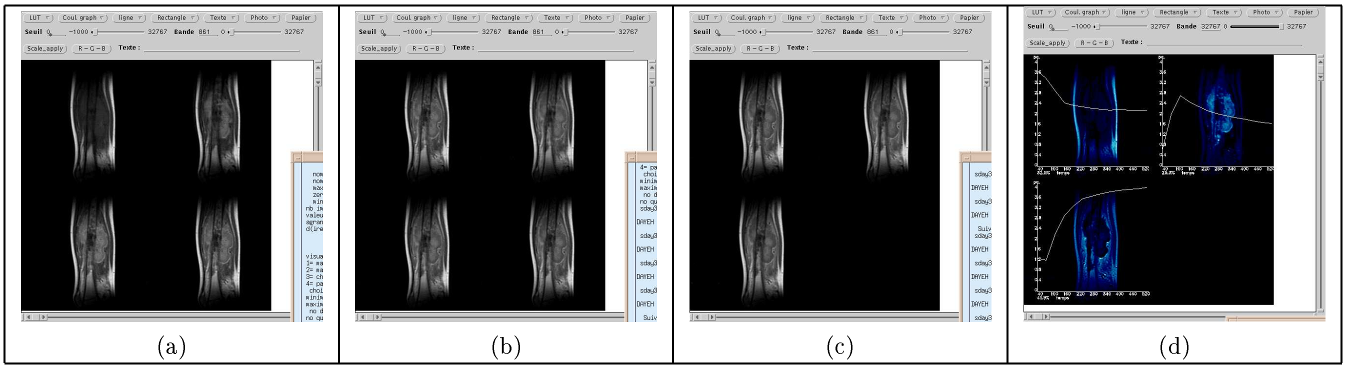

Figure 4: *MRI image sequence of tumoral knee in sagittal orientation and FAMIS results. (a) slices 1 to 4; (b) slices 5 to 8; (c) slices 9 to 11; (d) 3 resulting factors superimposed to their respective spatial localisation (early vascular factor, late vascular factor and accumulation factor in intersticial tissues)*

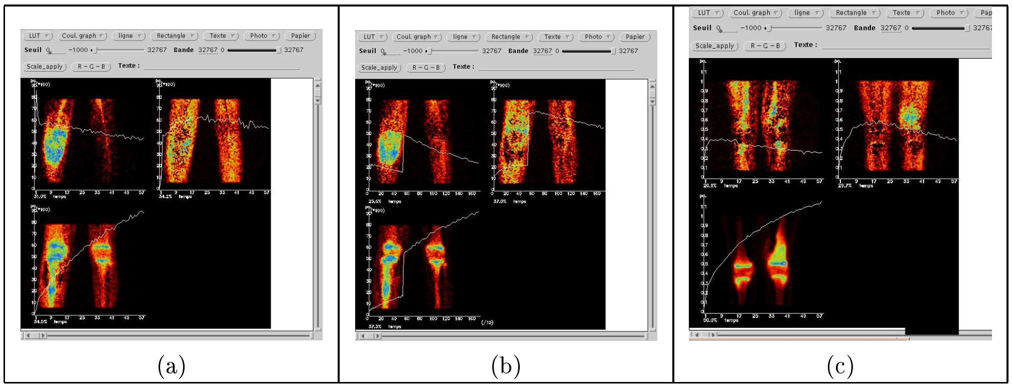

Figure 5: *FAMIS results on a NM image sequence of knees. On each three images the 3 resulting factors (early vascular factor, soft tissues factor and bony factor) are superimposed to their respective localisation. (a) shows results for a bad responder to chemotherapy; (b) shows results corrupted by patient's movement during image acquisition ; (c) shows results for the same sequence which movement has been previously corrected, thanks to the dynamic addition of a movement correction step before main processing.*

5 CONCLUSION

Based on the contents of the knowledge base and together with the description of data types such as a medical image sequence, we have developed a supervision engine to answer MIP needs, mixing hierarchical and reactive planning, as well as backtracking facilities. At present, we have developed a prototype version of a program supervision system for the FAMIS programs. The knowledge base contains the description of FAMIS main processing steps as well as the description of their organisation, constraints and links to executable programs. Available secondary steps are also described in such a way that they can be dynamically added in the processing if required by execution conditions.

The method has been successfully applied to the example of osteosarcoma chemotherapy follow-up. To the general methodological knowledge about FAMIS for dynamic sequences, we have added specific clinical knowledge concerning the use of FAMIS for this application. Given different input image sequences, the system is able to automatically adapt the processing so that the necessary programs are selected, ordered, and executed for successful processing of FAMIS. For instance, the system adapts the solution whether input sequence is NM and thus contains both knees, or MRI with only one knee and pre-injection image. This enabled us to experiment the ease with which such knowledge is taken into account by the supervision system on a well-defined procedure. The first results that we have obtained with this prototype are equivalent to those obtained manually by experienced clinicians. Moreover, the dynamicity of our planner and the richness of our data representation have proved to be adapted to MIP program supervision.

Our prototype offers program supervision facilities to clinical researchers as end-users, so they can explore FAMIS possibilities, freed from the management of FAMIS programs. Although the addition of strategic application-dependant clinical knowledge in the knowledge base is possible (as it has been partly done for osteosarcoma chemotherapy follow-up), the result in terms of lisibility and extension possibilities is not yet satisfying because knowledge levels are mixed. As a result, our prototype addresses the needs of clinical researchers by managing methodological knowledge, but not their needs for automatic exploration mechanisms (e.g. systematic trials, extra presentation facilities, learning mechanisms, etc.).

As a prospective work we intend to test the FAMIS knowledge base on other applications (e.g. tumor characterisation on MRI mammograms, NM/SPECT scatter correction) and develop new knowledge bases for other MIP programs (e.g. MRI-PET cardiac perfusion imaging), using the same program supervision engine. This will enable testing the extension possibilities of the knowledge base. We also intend to develop supervision mechanisms and knowledge concepts so as to better manage different kinds of reasoning, different evaluation possibilities and different levels of interaction.

Program supervision technique enables MIP experts to express their knowledge in such a way that it is explicit and thus can be transfered. Unlike procedural sets of instructions, the lisibility of MIP procedures elaborated with program supervision technique is increased. Moreover, easy extension possibilities and maintenance are facilitated, with respect to the rapidly evolving medical imaging environment: new procedures can be added, old can be easily changed. From end-users' point of view, a program supervision system is able to manipulate an abstract definition of a problem in clinical terms. Therefore, the diagnostic power of clinicians using (functional) image processing can be increased.

To conclude, the long term benefits of the program supervision technique are: (1) a reduction in the training required for clinicians, (2) a decreased variability in image processing and hence fewer clinical errors, (3) an improved standardisation such that the clinical results produced at one clinical centre can be compared with those obtained at another.

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