Computational Models for Image Guided, Robot-Assisted and Simulated Medical Interventions

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Abstract— **Medical Image Analysis plays a crucial role in the diagnosis, planning, control and follow-up of therapy. To be combined efficiently with medical robotics, Medical Image Analysis can be supported by the development of specific computational models of the human body operating at various levels. We describe in this article a hierarchy of these computational models, including the geometrical, physical and physiological levels, and illustrate their potential use in a number of advanced medical applications including image guided, robot-assisted and simulated medical interventions. We conclude this article with scientific perspectives.**

Index Terms— **Computational Models, Medical Robotics, Medical Image Analysis, Anatomical Models, Biomechanics, Physiological Models, Brain-shift, Augmented Reality, surgery simulation**

I. Introduction

Medical Imaging can be used for the planning and control of the motion of medical robots. Examples include the use of pre-operative images and geometric reasoning for path planning, the combined use of pre-operative and intra-operative images to control a surgical procedure with augmented reality visualization, or the simulation of surgical interventions on virtual organs built from pre-operative images and atlases with realistic visual and force feedback.

Such procedures require the use of advanced medical image analysis methods and the development of a hierarchy of so-called computational models of the human body [1]. These computational models aim at reproducing the geometrical, physical and physiological properties of human organs and systems at various scales (see Figure 1). They can be used in conjunction with medical images and robotics to actually enhance the possibilities of image analysis and robot control. The purpose of this article to describe first a hierarchy of levels of these computational models, and then to illustrate their potential use for medical robotics applications.

The first level is mainly *geometrical* and addresses the construction of digital static descriptions of the anatomy, often based on medical imagery. The techniques for segmenting and reconstructing anatomical and pathological structures from

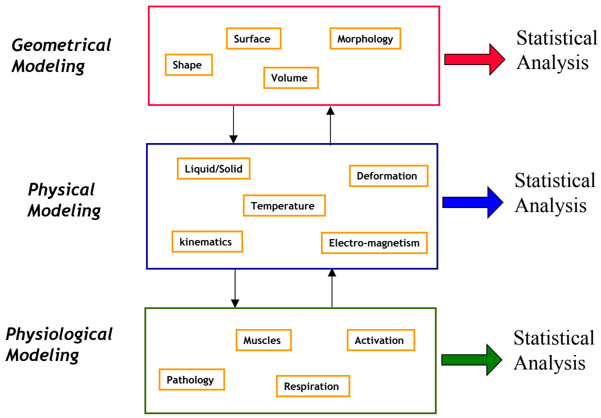


Fig. 1. Hierarchy of computational models of the human body (from [2])

medical images have been developed for the past 15 years and have brought many advances in several medical fields including computer-aided diagnosis, therapy planning, image-guided interventions, drug delivery, *etc*. An distinctive achievement of computational anatomy has been carried out by the "Visible Human Project" [3] which provided the first digital multimodal anatomical representation of the full human body.

A second level of modeling describes the *physical* properties of the human body, involving for instance the biomechanical behavior of various tissues, organs, vessels, muscles or bone structures [4].

A third level of modeling describes the functions of the major biological systems [5], [6] (e.g. cardiovascular [7], [8], respiratory [9], digestive, hormonal, muscular, central or peripheral nervous system, etc.) or some pathological metabolism (e.g. evolution of inflammatory or cancerous lesions [10], formation of vessel stenoses [11], [12], etc.). Such physiological models often include reactive mechanisms while physical models only provide a passive description of tissues and structures. A fourth level not depicted in Figure 1 would be cognitive, modeling the higher functions of the human brain.

Each model is specified by a number of parameters and a related task consists in studying the variability of those parameters across a given population. Thus, statistical modeling of those computational models can be seen as an orthogonal modeling activity that aims for instance at finding the local or global similarities and dissimilarities of a structure or a function between two populations [13], [14], [15]. Statistical findings may also be used to calibrate, refine or constrain [16] a given model. At the basis of this activity is the growing availability of large databases of subjects and patients including biomedical signals and images as well as genetic information.

There is an additional dimension associated with a given model : the scale at which the anatomical, physical or physiological structure is described. With the development of new imaging modalities, it is now possible to observe the shape or function of most structures at the macroscopic (tissue), microscopic (cellular) levels and even in such cases to reveal the metabolic activity a the nanoscopic (molecular) scale.

There is a distinction between *generic* and *specific* models. Generic models are useful for teaching [17] and for training [2] medical residents, especially when they include a variability study between normals and pathological subjects. There is also a growing need for patient-specific models whose parameters are adjusted to the actual geometrical, physical or physiological [18] properties of the considered patient. This is motivated by the evolution of medical practice toward more quantitative and personalized decision processes for prevention, diagnosis and therapy.

In the next sections, following our proposed hierarchy (geometrical, physical, physiological), we describe a number of computational models used for image-guided, robot-assisted and simulated medical interventions before proposing some perspectives and challenges for future research.

II. Geometrical Modeling

A. Extracting anatomical information from images

Medical images are the primary source of information for the reconstruction of the human anatomy and are particularly well suited for the creation of patient-specific models. They can be generated by various imaging systems (MR, CT, US) and may have different dimensions (2D, 3D or 3D+t). The extraction of the geometrical description from those images requires the application of image segmentation algorithms that can generate a large variety of geometrical description of the targeted structure. The nature of the geometrical representation largely depends on the application. For instance, the volume rendering of a patient anatomy only requires to label the voxel belonging to the region of interest and to define its opacity function. For image-guided therapy a surface mesh of the structure is often sufficient while other therapy planning applications may need the definition of a volumetric mesh based on tetrahedra or hexahedra [19].

There exist many pitfalls when creating meshes from medical images. For instance, the transformation of a segmented image into a surface mesh often requires using the Marching Cube algorithm [20] which tends to create a large number of poorly shaped triangles. Mesh decimation [21] is then applied to drastically reduce the number of elements and improve their shapes. Other meshing techniques [22] are being developed that aim at directly producing a small number of well-shaped triangles from isosurfaces.

For volumetric meshes, the quality of the elements is especially of great importance since it influences the time of convergence and even the convergence of the simulation. Even if hexahedral meshes usually lead to more accurate results than tetrahedral meshes [23] for the same number of nodes, their grid topology makes them ill-suited to represent complex shapes, unless a gross approximation of the surface is tolerated. The construction of patient-specific volumetric meshes can be produced from images in two ways. The first approach is bottom-up and consists in automatically filling a triangulated surface with tetrahedra [24], [25] or generating hexahedra from a set of voxels. The second approach is top-down and relies on a registration technique to deform a generic tetrahedral [26] or hexahedral mesh [27] towards the segmented region in the image. The deformation of a generic model serves to automatically label mesh parts corresponding to specific boundary conditions, or specific material properties [26].

B. Hepatic Surgery Planning

Many state-of-the-art medical applications in clinical use rely on static anatomical models. For instance, we have developed [28] an automated hepatic surgery planning system that helps surgeons to choose a surgical strategy. This system can be used on a laptop during the intervention to improve the control of skill.

To acquire a knowledge of the patient anatomy, radiologists use CT-scans, which are acquired 60 seconds after the intravenous injection of a contrast medium. Theses images allow the visualization of hepatic tumors and contrasted vessels as well as the liver. We have developed a method which provides the segmentation of the following abdominal structures from a high resolution CT-scan within 15 minutes : skin, bones, lungs, heart, aorta, spleen, kidneys, gallbladder, liver, portal vein and hepatic tumors greater than 5 mm diameter (see Figure 2). Note that other hepatic surgery planning systems [29], [30] have also been proposed.

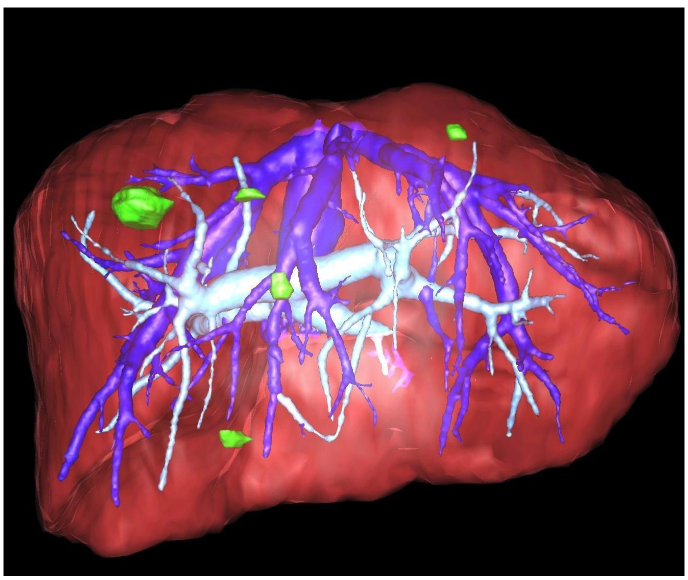


Fig. 2. Reconstructed liver from the patient CT scan image (from [28]).

C. Augmented Reality

Anatomical models are important not only for planning a therapy but also for guiding the execution of that therapy. This requires the additional task of relating the pre-operative plan coordinate system to the physical space where the patient actually lies. When the therapy is robot-assisted, this geometric correspondence and the anatomical knowledge of surgical field can be used to optimize the port placement [31] or to define safety zones [32] where the tip of the robot should not move. Similarly, Augmented Reality provides a convenient and efficient steering of the gesture by overlaying the pre-operative information onto real intra-operative views of the patient [33]. Augmenting the surgeon's view with this information may lead to a better understanding of the pathology and decision process during the intervention [34]. By tracking also the surgical tools in real time, or by robotizing them [35], one can also guide surgeons more efficiently along the planned path toward the virtual target.

Most applications developed so far are dedicated to neurosurgery and orthopedic surgery, since bones offer very reliable landmarks to register the virtual patient to the real one [36], [37], [38]. More recently, techniques based on the specific geometry of the intra-operative acquisition device were proposed for the chest or the abdomen, for instance to superimpose fluoroscopic images onto video images of the patient [39]. Other examples are given by the use of semi-transparent mirrors to display ultrasound [40], [41] or CT slices [42], in such a way that images appear naturally registered to the patient.

However, these augmented reality techniques only superimpose intra-operative images onto video images of the patient. To display pre-operative information, one needs to register those images to the patient geometry. For instance, we have developed [43] an augmented reality system for needle in-

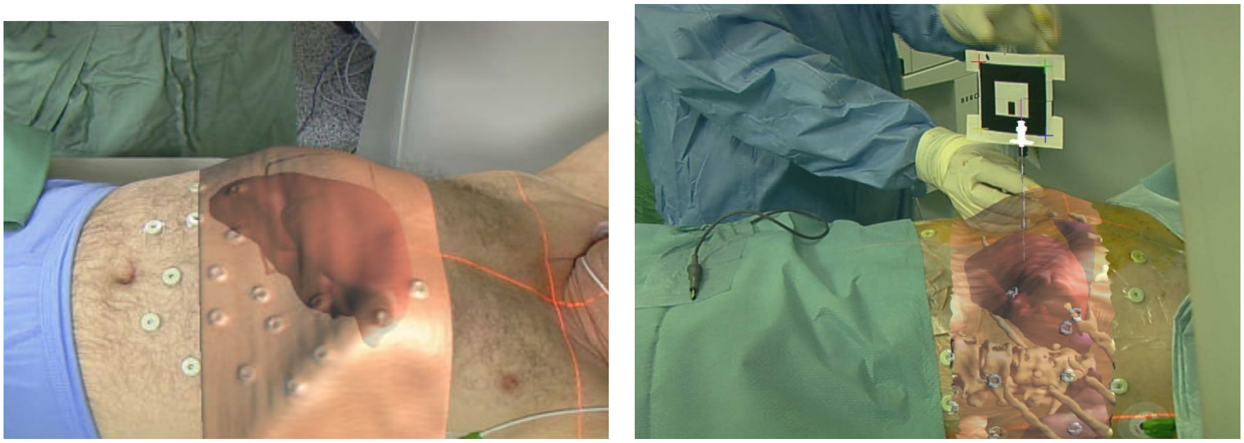


Fig. 3. (Left) Augmented reality based on 3D radio-opaque markers; (Right) Augmented view of patient at the tip of the needle (from [43]).

sertion guidance in hepatic radio-frequency ablation. This system superimposes in real-time 3D reconstructions from CT acquisitions and a virtual model of the needle on real video views of the patient, thanks to the 3D/2D registration of radio-opaque markers stuck on the patient skin (see Figure 3).

D. Registration : a central issue

A careful evaluation of the performances of the registration algorithm [44] is essential for augmented reality since some pre-operative information is used as a substitute for hidden information in video images: a registration error may lead the surgeon to miss the real target, with potential collateral damages.

Registration is basically an optimization procedure which aims at finding the best transformation parameters. It can be evaluated in terms of robustness, precision and accuracy. First, one can distinguish between gross errors (convergence to wrong local minima) and small errors around the exact transformation. *Robustness* is the ability to converge to the right minimum, and may be quantified by the size of the basin of attraction, or the probability of false positives. Small errors around the right transformation might have a systematics trend (a *bias*), in which case the variance around the mean (characterizing the *precision or reproducibility*) is much smaller than the variance w.r.t. the ground truth (characterizing the *accuracy*). This distinction is important as one most often misses the ground truth to evaluate the performances of registration algorithms. In that case, one is left with the quantification of the precision, which can be significantly smaller than the real accuracy [45]. Accuracy is an important concern in image guided therapy, and is indeed difficult to evaluate [46]. In some cases, however, one can certify the quality of the registration result in real-time, which allows to dynamically adapt the surgical procedure in order to reach the maximal safety [47].

In terms of routine use of guidance systems in clinics, robustness can be even more important than accuracy, as rare but large errors may lead to much more dramatic consequences than a slightly larger average error. As a perfect robustness is not achievable, *fault detection* is thus of the upper importance. However, this is a very difficult problem: thanks to his anatomical interpretation of the image, a human observer immediately sees when the registration grossly fails, whereas the algorithm only knows that it is in a local minimum of a cost functional! Thus, providing a friendly user interface for the clinician to supervise and possibly interact to correct the registration results is often the key for the use of image guided systems in clinical environments [48].

Last but not least, registration algorithms have to be real-time in the image guided surgery context. By real-time, one means that the computation time should be significantly shorter than the typical motion time (a few minutes for the brain shift, a few tenths of second for the beating heart), the limiting factor being often the acquisition of the intra-operative images (e.g. 2 minutes for open MR in brain-shift compensation). In some cases, one might find some theoretical approximations that drastically speed-up the algorithm [49]. However, one relies in most cases on the parallelization of the algorithm in order to reach a computation time compatible with the clinical constraints [50], [51].

III. Biomechanical/Physical modeling

Anatomical models only provide a static geometrical representation of the patient anatomy and do not take into account the deformation of soft tissue that may occur before or during therapy. To address this issue, it is necessary to add a biomechanical model that can estimate soft tissue deformations under the application of known forces or displacements. The additional complexity of modeling may be used to improve the pre-operative planning of a therapy [52], [53] or to provide advanced surgical gesture training as illustrated in the sections below. Note that there are also important research efforts involving physical but non-mechanical phenomena for instance for the planning of radiotherapy or radiofrequency ablation [54].

A. Brain-Shift modeling in neurosurgery

The brain shift that occurs during a neuro-surgical intervention is the main source of intra-operative localization inaccuracies of pathologies (cerebral tumors,...). Indeed, a neurosurgeon establishes the surgical plan based on a pre-operative MR image : any non-rigid motion of the brain between the pre-operative and the intra-operative configuration may lead to an error in the localization of the target. This clinical problem has motivated the study of the biomechanical behavior of the brain [55]. To model the brain motion after opening the dura, a number of authors [56], [57] have made the hypothesis that the loss of cerebro-spinal fluid causes a pressure field along the gravity direction (Archimedes principle). Furthermore, anatomical constraints (falx cerebri, skull) of the deformation field can be enforced with a biomechanical model of the brain discretized as a tetrahedral mesh since the relevant anatomical information can be extracted from MR images and enforced on the mesh. The predictive power of some models has been shown for instance for methods extrapolating displacement fields [57], [58] from the cortex surface. Also, partial validation of brain shift models may be carried out [59] by comparing computed displacements with those observed from intra-operative MR images.

Conversely, it interesting to stress that when validated, those biomechanical models can be used to register pre-operative and intra-operative MR images [57], [60] of the same patient in an efficient (near real-time) and realistic way. Thus modeling brain tissue deformation leads to solving both direct (or predictive) and inverse (or estimation) problems and we propose to describe this global interaction as coupling biomechanical models with medical images.

B. Surgery Simulation

Surgery simulation aims at reproducing the visual and haptic senses experienced by a surgeon during a surgical procedure, through the use of computer and robotics systems. The medical scope of this technology is linked with the development of minimally invasive techniques especially videoscopic surgery (endoscopy, laparoscopy,...) and possibly telesurgery. Because of the limitations of current training methods, there is a large interest in developing video-surgery simulation software for providing efficient and quantitative gesture training systems. Indeed, such systems should bring a greater flexibility in the training by providing scenarios including different types of pathologies. Furthermore, by creating patient-specific models, surgery simulation allows surgeons to verify, optimize and rehearse the surgical strategy of a procedure on a given patient.

Building a surgical simulator requires the real-time and realistic simulation of soft-tissue deformations. More precisely the required refresh rate for user interaction is 30 Hz for visual feedback and more than 500 Hz for force-feedback, although the latter constraint can be alleviated with the addition of a local haptic model [61], [62]. Authors have proposed several soft tissue models trying to combine realism with efficiency. Discrete models such as spring-mass models are simple to implement but generally fail to produce realistic deformations [63].

Combining finite element modeling and continuum mechanics has also been a popular approach which has provided advanced soft tissue simulation. Linear elasticity provides a simple and realistic framework when soft tissue undergoes small deformations. By exploiting the principle of superposition, one can precompute [2], [64], [65] the displacement field produced by applying a set of surface forces for an anisotropic and inhomogeneous material. This very efficient scheme (leading to a 500 Hz refresh rate or more) is however not compatible with mesh topological changes that are involved when simulating tissue resection. Tensor-mass models [66] provide realistic volumetric deformations while authorizing topological changes (cuttings) with a complexity similar to spring-mass models.

To handle large deformations, one must introduce non-linear elastic models with the drawback of larger computational cost. To reach real-time computation, authors have proposed non-linear tensor-mass models [2], [67], multigrid [68] and co-rotational approaches [69] each having its advantages and limitations in terms of computational efficiency, topological adaptation and deformation realism. Similarly, meshless methods [70] are an interesting alternative to finite element methods where the location and the number of nodes can be optimized.

An important issue related to those models is the estimation of material properties such as the Young Modulus for linear elastic material or the stress-strain relationship for hyperelastic ones. There are three different sources of rheological data : *ex-vivo testing* where a sample of a tissue is positioned inside a testing rig [71], [72]; *in-vivo testing* where a specific force and position sensing device is introduced inside the abdomen to perform indentation [73], [74]; *Image-based elastometry* from ultrasound, Magnetic Resonance Elastometry [75], [76] or CT-scan imaging.

There is no consensus on which method is best suited to recover meaningful material parameters. For instance, the rich perfusion of the liver affects deeply its rheology (the liver receives one fifth of the total blood flow at any time) and therefore it is still an open question whether *ex-vivo* experiments can assess the property of living liver tissue, even when specific care is taken to prevent the swelling or drying of the tissue. Conversely, data obtained from *in-vivo* experiments should also be considered with caution because the response may be location-dependent (linked to specific boundary conditions or non-homogeneity of the material) and the influence of the loading tool caliper on the deformation may not be well understood. Furthermore, both the respiratory and circulatory motions may affect *in-vivo* data.

Another difficult task when implementing a surgical simulation includes the detection and computation of collisions between a deformable model and rigid bodies [62] or between several deformable bodies [78] (see Figure 5).

Fig. 5. Simulation of an intervention on a human intestine [78] that involves complex handling of self-collisions (courtesy of M-P. Cani).

IV. Physiological Modeling

Up to now, we showed that geometrical and physical/biomechanical modeling of the human body provide representations allowing geometric reasoning, navigation, and various forms of simulated interactions including deforming and cutting soft tissues with realistic visual and haptic feedback. However the tissues and organs still behave like passive material, and it is necessary to go one step further to model the active properties of living tissues and the dynamic nature of normal or pathological evolving processes. We illustrate this level of modeling with two examples related to the modeling of the electro-mechanical activity of the heart and the growth of brain tumors. Additional examples related to the modeling of physiological flows can be found in [11], [12], [79].

A. Cardiac modeling

During the past 5 years, a scientific INRIA consortium regrouping internal and external research teams[1] has developed an electro-mechanical model of the cardiac ventricles

[1] cf. CardioSense3D URL http://www.inria.fr/CardioSense3D/

Fig. 4. (Left) A force feedback system suited for surgery simulation; (Right) View of the simulated hepatic resection involving linear-elastic materials (from [2], [64], [66] and [77], [62]).

for medical purposes. The model reproduces the electrical depolarization and repolarization of the cardiac tissues through a set of macroscopic reaction-diffusion equations initially proposed by Fitzugh and Nagumo [80] and further refined by Aliev and Panvilov [81]. This electrical activity, which can be synchronized with the actual ECG (electro-cardiogram) of the patient, creates a mechanical contraction followed by an active relaxation which are modeled by a set of partial differential equations initially proposed by Bestel, Clement and Sorine [82].

It was shown in [8] that this model could be interactively adjusted to the actual geometrical, mechanical or electrical properties of patient's heart through the use of conventional or tagged MR images and some *in vivo* electrophysiological measurements. The average direction of the myocardium fibers is also integrated into this model, because it plays an important role in both the electrical and mechanical modeling. Even more interestingly, the model can then be used to study the effect of modifying locally some electrical or mechanical properties in order to better predict the effect of a therapy or the evolution of a pathology [83], [84] (see Figure 6).

We believe that this kind of models of a dynamic organ could be used in the future to better plan or train a number of medical skills for instance in radiofrequency ablation procedure, for the positioning of stimulation probes of pacemakers, and maybe in the long term future to simulate beating heart with the potential use of robotics [85].

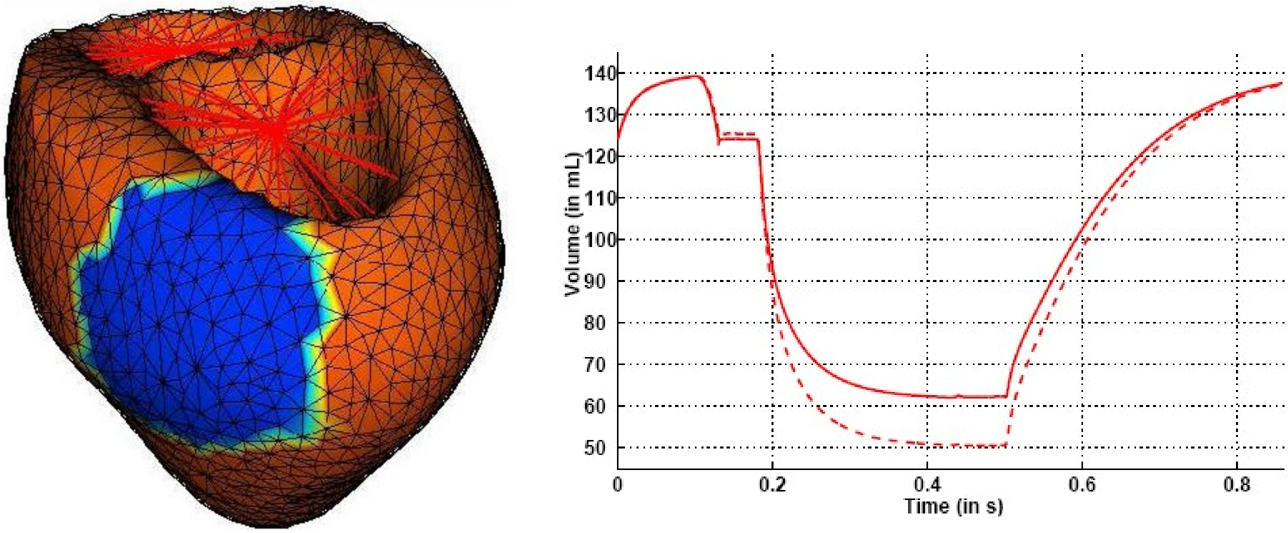


Fig. 6. Predicting the effect of pathologies with an electro-mechanical model of the heart [8]; (Left) Definition of a basal left epicardial infarcted zone (no conduction and no contraction in that area) shown in blue; (Right) Curves of ejected volume during a cardiac cycle without (dashed) and with (solid) infarct. The ejection fraction decreases from 65% to 55%.

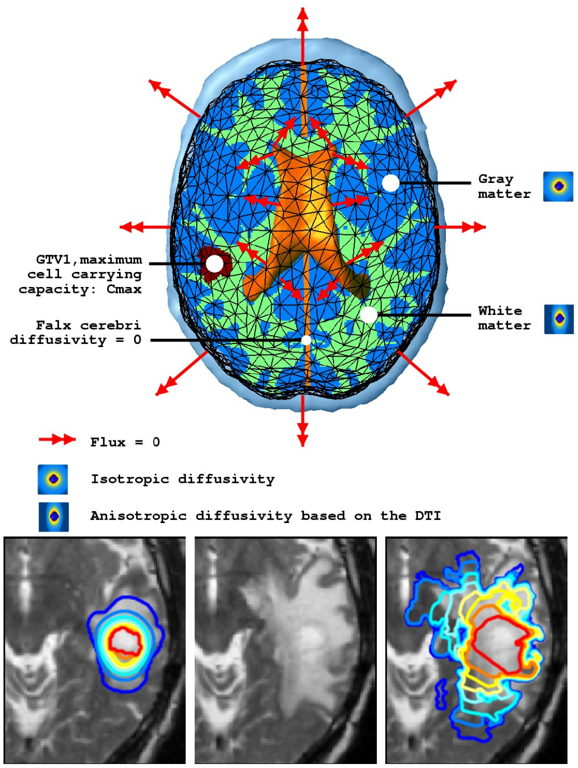
B. Tumor growth

The second example is related to the modeling of the growth of brain tumors. A joint action between INRIA, a Nice Hospital (Centre Antoine Lacassagne) and the Brigham and Women's hospital (Boston) has led to the development of a three level model [86].

The first level includes the geometrical model of a patient's head, including the skull, the brain parenchyma (grey and white matter) and the Cerebro-Spinal Fluid (CSF). The shape of each region is acquired through a conventional MR exam. In addition, the direction of the main white matter fibers is also acquired either through Diffusion Tensor Imaging (DTI), or using average directions provided by a brain atlas. A second level includes the modeling of the biomechanical properties of the brain tissues. Because we are considering small deformations only, this model is a linear elastic one, and implements the boundary conditions imposed by the bony (skull) and fluid (ventricles) structures surrounding the brain parenchyma. The third level is an evolution model of the tumoral tissues, which is based on a set of reaction-diffusion equations describing the proliferation and diffusion of malignant cells [87].

An original point is the coupling of the third level with the previous two levels in order to create a realistic deformation of the brain tissues (also called *mass effect*) produced by the tumor growth. The direction of the white matter fibers plays an important role in the highly anisotropic diffusion of cancerous cells (see Figure 7).

We believe that this type of model will prove to be quite useful to predict the evolution of a pathology from a number of observations made at a limited number of time points. It will help the guidance of medical strategies (e.g. radiotherapy, surgery) in predicting more precisely the boundaries of



(a) (b) (c)

Fig. 7. (Top) Overview of the evolution model of cancerous cells which takes into account the anisotropic diffusion along white matter fibers; (Bottom) Result of the tumor growth simulation on a brain slice; (a) Initial MR T2 image of the patient with lines of constant tumor density; (b) View of the corresponding MR T2 slice (after rigid registration) six months later; (c) Lines of constant tumor density predicted by the tumor growth model [86] after 6 months of evolution.

pathological tissues.

V. Summary and Perspectives

We have shown in this article how computational models of the human body could be used in conjunction with medical imaging techniques to assist in the preparation, simulation and control of medical interventions. A key point is the possibility offered by these models to actually fuse the geometrical, physical, and physiological information necessary to provide a thorough and reliable analysis of the complex and multi-modal biomedical signals acquired on each patient, possibly at various scales.

We list below some research topics that should open new perspectives in improving medical practice :

- *Statistical Analysis*. The development of large databases of medical images should further improve the robustness and accuracy of the previously discussed computational models, and therefore the performances of image-guided intervention or simulation systems.
- *Soft Tissue Modeling*. The development of sophisticated *ex-vivo* and *in-vivo* indentation devices should lead to a better understanding and new mathematical models of the mechanical behavior of human organs. In the context of surgery simulation, further optimization in soft tissue deformation is required to simulate a whole surgical intervention and not only a series of surgical tasks.
- *Real-time Coupling of Models with Observations*. This requires very fast inversion of realistic computational models. This will improve robot-assisted image-guided therapy in the presence of patient motion (brain shift, respiration, cardiac motion, etc). Figure 8 previews the combination of augmented reality (geometrical models) with medical robotics.
- *Miniaturized Robotics* The advances in robotics research, in particular the design of new generations of highly accurate, easy-to-use miniature robotic guidance systems (e.g. the spine-assist system [88]) might also contribute to the successful combination of computational models and medical imaging.
- *Microscopic Imaging*. New *in vivo* microendoscopy tech-

Fig. 8. By combining Augmented reality (left) and robotics (right) accuracy of image guided surgery may be improved and this may lead to additional levels of surgical automation (from [34]).

niques [89], [90] providing structural information on the tissues at the cellular level should also open, combined with robotics and computational models, new avenues for improving diagnosis and therapy.

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