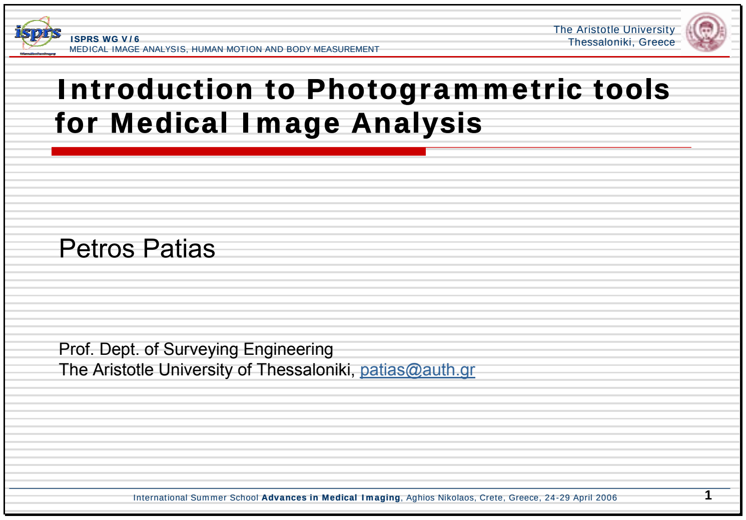
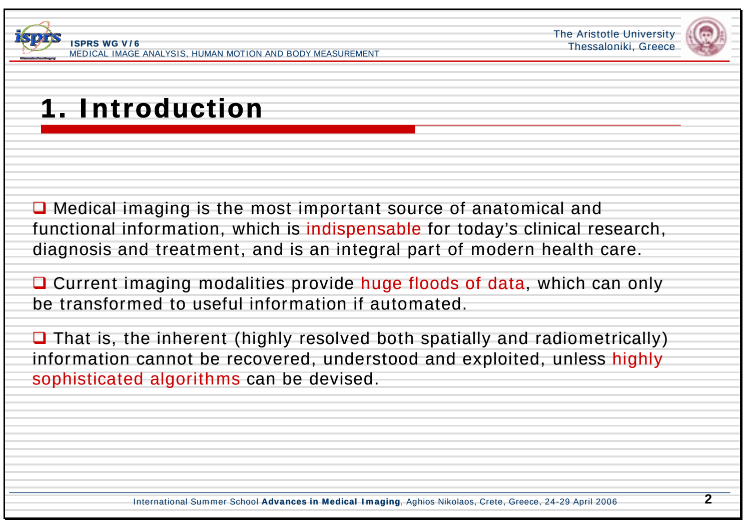




1. Introduction

Medical imaging is the most important source of anatomical and functional information, which is indispensable for today's clinical research, diagnosis and treatment, and is an integral part of modern health care. Current imaging modalities provide huge floods of data, which can only be transformed to useful information if automated. That is, the inherent (highly resolved both spatially and radiometrically) information cannot be recovered, understood and exploited, unless highly sophisticated algorithms can be devised. Therefore, both medical imaging and the automated interpretation of imagery are of central importance today.

Most of the clinically evolving abnormal situations are actually evolving in space, i.e. they are 3D processes. There are numerous parameters inherent to these 3D processes, that have in general been understudied and have the potential to better delineate the actual pathologic process and probably contribute significant prognostic information. Therefore, accurate 3D-information extraction is fundamental in most of the situations.

Such conclusions inevitably underline the importance of the technology transfer across disciplines. Indeed, it is this technology fusion among different disciplines that has changed enormously medical diagnosis and treatment in recent years.

In this quest for more accurate 3D reconstructions and more robustness of the automated processes, photogrammetry has an important role to play. Although, up to now, photogrammetric contributions were aiming mainly at the reconstructions of the outer body using optical sensors, the mapping of the internal body presents a much greater research area; both in terms of scientific challenge and in terms of the wider range of applications.

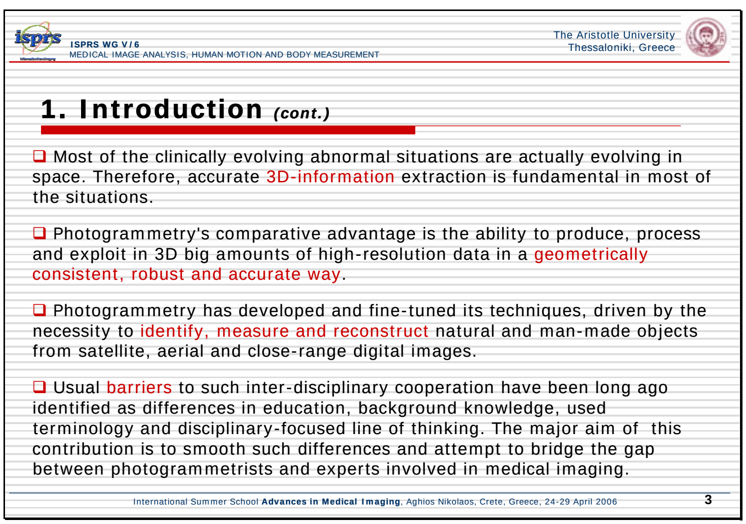
Photogrammetry's comparative advantage is the ability to produce, process and exploit in 3D big amounts of high-resolution data in a geometrically consistent, robust and accurate way. During its course, photogrammetry has developed and fine-tuned its techniques, driven by the necessity to identify, measure and reconstruct natural and man-made objects from satellite, aerial and close-range digital images. This gave a considerable growth to photogrammetry and established it as the method of choice for a wide range of applications.

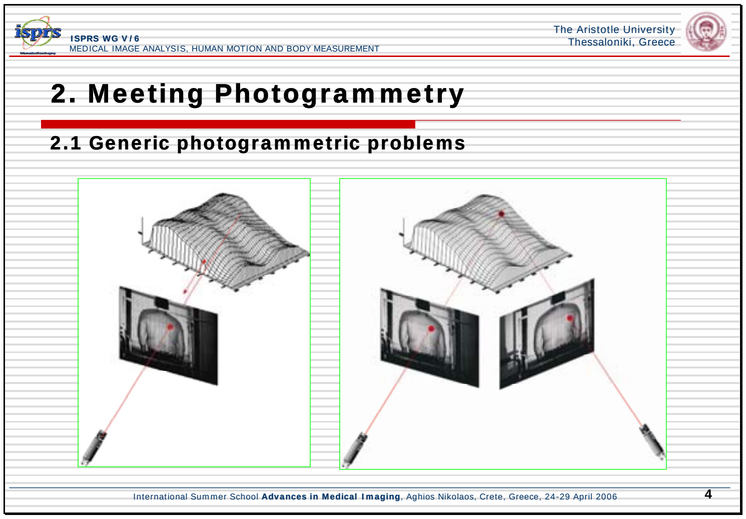
In many respects, current challenges in medical imaging show remarkable similarities to usual photogrammetric problems. Towards their solution, photogrammetry has the potential to highly contribute and bring new level of understanding, once a cross-disciplinary understanding is established.

Usual barriers to such inter-disciplinary cooperation have been long ago identified as differences in education, background knowledge, used terminology and disciplinary-focused line of thinking. The major aim and intended contribution of this paper is to smooth such differences and attempt to bridge the gap between photogrammetrists and experts involved in medical imaging.

In doing that, the paper is structured in two main parts. In the first part, a general account of the principal ideas underlying the photogrammetric practice is presented. The purpose is to provide the non-photogrammetrists with a basic understanding of both the main course as well as the terminology of photogrammetry. Additionally, it aims at establishing a basic and realistic background of what can be expected from these techniques.

The second part is devoted to the presentation of major challenges in medical imaging. The major apparent aim is to familiarize photogrammetrists, this time, with the basic problems, terminology, literature, and research trends in medical imaging. On purpose, these problems are presented in their basic configuration and in generic terms, in order to provoke photogrammetrically understood research questions. By no means this presentation is exhaustive. It is only meant to highlight some major problems and pinpoint the possible contributions from the part of photogrammetry.



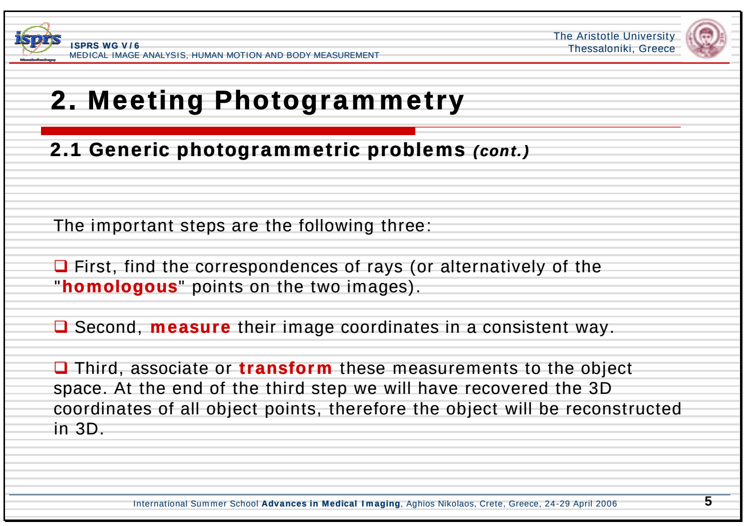


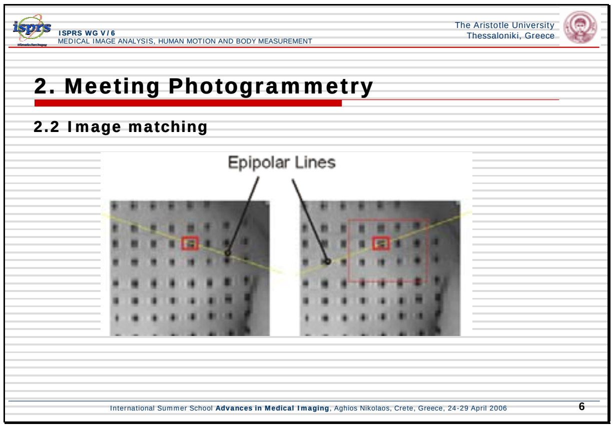
2. Meeting Photogrammetry

2.1 Generic photogrammetric problems

In generic terms, photogrammetry tries to reconstruct 3D objects from their 2D images. Supposing that an image consists of the "projections" of all object points through "lines-of-sight", the image plane is merely a section of this bundle of rays in space. Along every line a corresponding object point can be determined, but since all the space points along this line will project at the same point on the image plane, this determination is not unique and the 3D coordinates of the object point cannot be recovered. However, if we introduce another image (Fig. 1) the object point will be uniquely defined as the intersection of the two corresponding rays. Additional images will add additional rays, but the point will still be the unique intersection of all corresponding rays.

The important steps now are the following three: First, find the correspondences of rays (or alternatively of the "homologous" points on the two images). Second, measure their image coordinates in a consistent way. Third, associate or transform these measurements to the object space. At the end of the third step we will have recovered the 3D coordinates of all object points, therefore the object will be reconstructed in 3D.

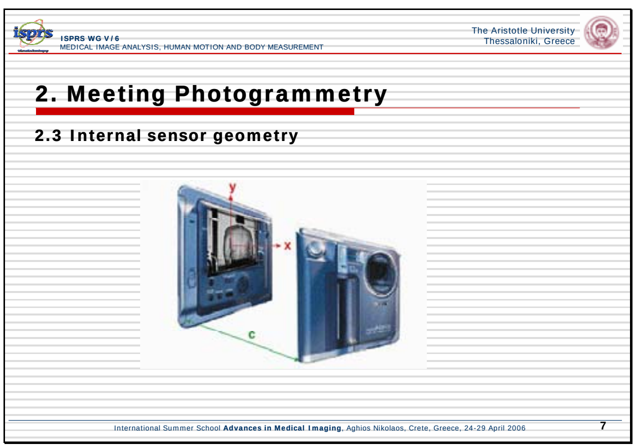




2. Meeting Photogrammetry

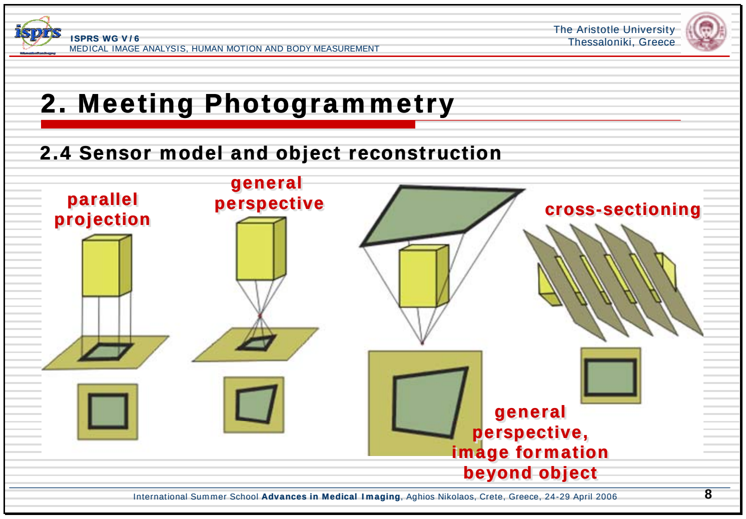
2.2 Image matching

The first step clearly involves the correct "matching" of all image points of the left image to their counterparts in the right image. In doing that, photogrammetry uses a number of sophisticated techniques, which involve both radiometric (e.g. measures of similarity of grey values) and geometric constraints (e.g. relative orientation of one image with respect to the other, see Fig. 2) in order to find all matches, minimizing the "false alarms" at the same time. Additionally, it uses a least squares estimation procedure, which also accounts for measurement errors and provides statistically valid indications of the "correctness" of the matches.



2.3 Internal sensor geometry

The second step requires first the definition of a consistent coordinate system on each image, to which each image point measurements will refer. Such a coordinate system also relates the image points to the centre of the sensor system. This way all image points will have plane coordinates (x, y) as per measured and a "virtual" third dimension (c) equal to the "focal length" of the sensor system. Additionally in this step possible image distortions, due to imperfect sensors, will be corrected according to sensor calibration information. In case such information is not provided, these errors will be modelled later on (see 2.4).



2.4 Sensor model and object reconstruction

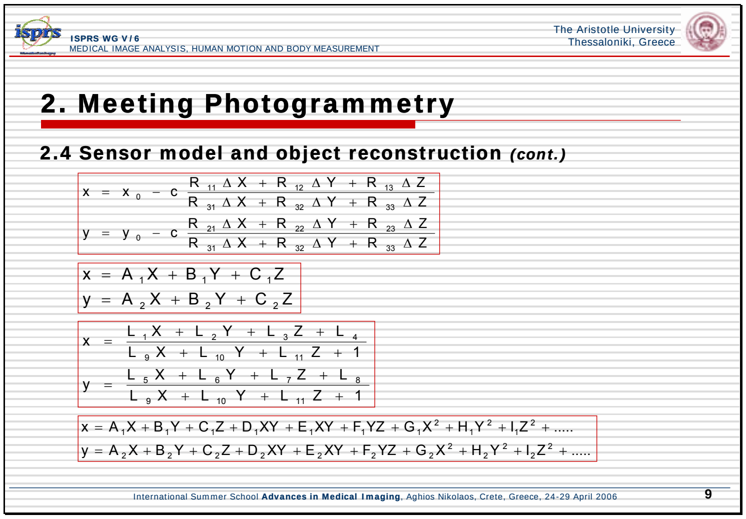
Thus, for each object point we have a set of image coordinates (x1, y1, c), (x2, y2, c) corresponding to (at least) two homologous points on the related images. The third step now involves the transformation of these coordinates to a unique triplet (X, Y, Z) for each object point. In doing that we need to know how the image has been formed, by what mechanism the bundle of rays have been generated; in other words, how does the sensor "map" the real world. We call it the "sensor model" and it relates the "image space" to the "object space".

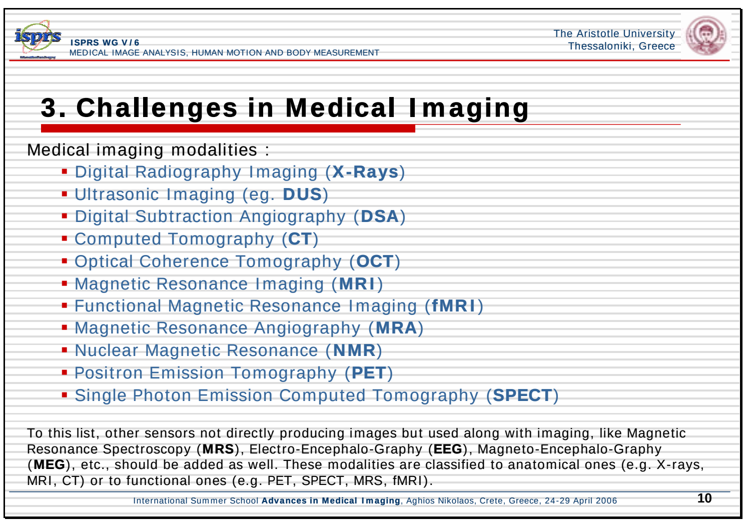
Fig. 3 shows typical such models: Fig. 3a shows a parallel projection (as for example in ultrasound images), Fig. 3b shows the most used general perspective projection, including sensor tilts (i.e. all images acquired through a lens system), Fig. 3c shows a variation of 3b, where the image is formed beyond the object (i.e. as in X-raying) and finally Fig. 3d refers to images formed by cross-sections of the images (i.e. as in CT or MRI. Note that many biomedical 3D reconstructions originate from 2D slices in various orientations (axial, sagittal, coronal, etc.), which are reconstructed by back-projection (e.g. CT, PET or SPECT) or direct 3D reconstructions (e.g. MRI).

In all different cases the same object (in our example: a perfect square) is imaged distorted but in a different manner each time. To these distortions, one should also add distortions caused by imperfections of the sensor system itself (see 2.3), which, to a first approximation and for the economy of our discussion, can be considered linear (i.e. affine). Therefore, the real image each time will have the form shown at the bottom line of Fig. 3. And we are called to "deduce" the 3D coordinates of a perfect square from "correct" (plus measurement errors) measurements on "imperfect" images.

This is a central problem in photogrammetry, which is being solved by describing the geometry of the sensor model through analytic formulation. For example Eq. (1) describes the perspective projection of Fig. 3b, 3c; Eq. (2) describes the geometry of Fig. 3a accounting also for affine sensor distortions; similarly, Eq. (3) describes the geometry of Fig. 3b, 3c accounting also for affine sensor distortions. If we pretend that we know nothing about the way the sensor forms the image, or if the actual sensor geometry is too complex to be analytically described, then the only option left is to use a generic and rather "blind" formulation, like the one in Eq. (4). In this we admit that the image is formed in an unknown to us way and thus any kind of distortion is possible (linear plus non-linear). To the degree that this is not actually the case, that assumption may lead to irregular solutions and awkward figures. Thus, it is always much safer to explore and correctly model the actual geometry of the involved sensor.

The interested reader can refer to either standard photogrammetric textbooks (like Mikhail et al., 2001), or to more specific ones, dealing with close-range photogrammetry (like Atkinson, 1996 or Karara, 1989). A useful reference is also the Theme Issue “Photogrammetry and Remote Sensing in Medicine, Biostereometry and Medical Imaging” of the ISPRS Journal of Photogrammetry and Remote Sensing, Vol. 45, No. 4, 1990.





3. Challenges in Medical Imaging

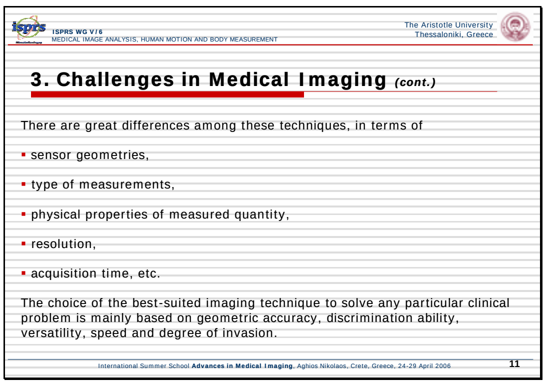
Modern healthcare practices are increasingly depended on data and information captured and processed by a wide range of medical imaging modalities, like Digital Radiography Imaging (X-Rays), Ultrasonic Imaging, Digital Subtraction Angiography (DSA), Computed Tomography (CT), Optical Coherence Tomography (OCT), Magnetic Resonance Imaging (MRI), Functional Magnetic Resonance Imaging (fMRI), Magnetic Resonance Angiography (MRA), Nuclear Magnetic Resonance (NMR), Positron Emission Tomography (PET), and Single Photon Emission Computed Tomography (SPECT), see e.g. (Klingenbeck and Rienfelder, 1990). To this list, other sensors not directly producing images but used along with imaging, like Magnetic Resonance Spectroscopy (MRS), Electro-Encephalo-Graphy (EEG), Magneto-Encephalo-Graphy (MEG), etc., should be added as well. These modalities are classified to anatomical ones (e.g. X-rays, MRI, CT) or to functional ones (e.g. PET, SPECT, MRS, fMRI).

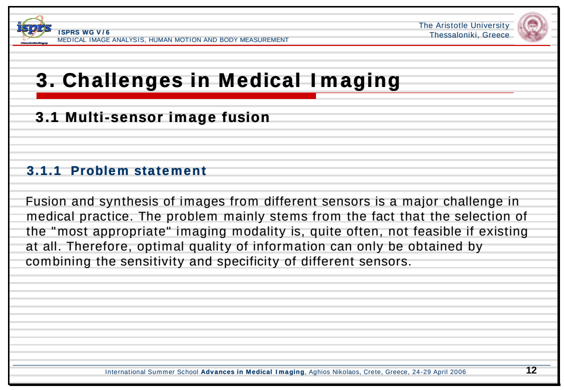
There are great differences among these techniques, in terms of sensor geometries, type of measurements, physical properties of measured quantity, resolution, acquisition time etc. The choice of the best-suited imaging technique to solve any particular clinical problem is mainly based on geometric accuracy, discrimination ability, versatility, speed and degree of invasion. However, the imaging procedure itself, although important, is only the first step in this process.

Converting data to useful and meaningful information is the next equally important step towards diagnosis and treatment.

In the next sections we will try to group and analyse, in generic terms, the major problems and challenges Medical Imaging is facing, while pursuing this second step. We recognize that this classification is neither easy nor exhaustive. However, it highlights, in generic terms, the otherwise vast and detailed medical research efforts and the related literature.

The major aim of this analysis is to pin-point the grand challenges in medical imaging practice and describe them in photogrammetric terms in a productive way - meaning a way that attracts photogrammetric interest and also been subjected to solutions along the photogrammetric line of thought.





3.1 Multi-sensor image fusion

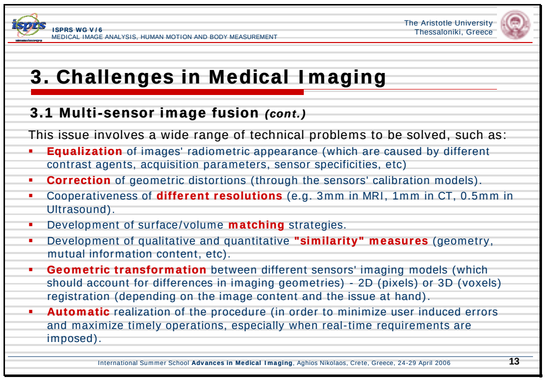
3.1.1 Problem statement

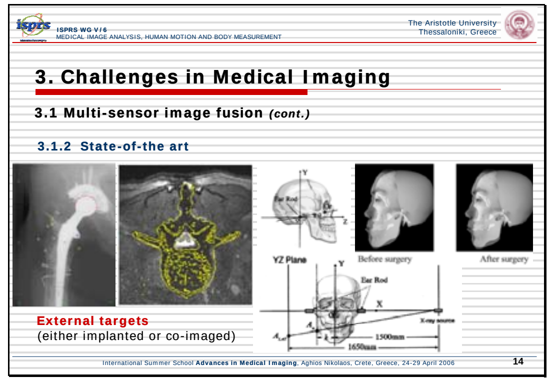
Fusion and synthesis of images from different sensors is a major challenge in medical practice. The problem mainly stems from the fact that the selection of the "most appropriate" imaging modality is, quite often, not feasible if existing at all. Therefore, optimal quality of information can only be obtained by combining the sensitivity and specificity of different sensors.

A classical example in terms of image contents is CT/MRI fusion: CT images provide excellent contrast of bones and other dense structures (high intensity values) to the surrounding tissue, whereas MRI images soft tissues very well and only poorly the bones. However, the visualization of the spatial relationships of both is very useful in many clinical areas (e.g. spinal pathologies – vertebral bodies and disks, nerves, etc.). The benefits are even more profound in combining anatomical imaging modalities with functional ones, e.g. PET/CT in lung cancer, MRI/PET in brain tumors, SPECT/CT in abdominal studies, Ultrasonic Images/MRI for vascular blood-flow, etc.

However, the maximum clinical value of such image fusion can be realized only if an accurate multi-image registration is available. Clearly, this issue involves a wide range of technical problems to be solved, such as:

- Equalization of images' radiometric appearance (which are caused by different contrast agents, acquisition parameters, sensor specificities, etc)
- Correction of geometric distortions (through the sensors' calibration models).
- Cooperativeness of different resolutions (e.g. 3mm in MRI, 1mm in CT, 0.5mm in Ultrasound).
- Development of surface/volume matching strategies.
- Development of qualitative and quantitative "similarity" measures (geometry, mutual information content, etc).
- Geometric transformation between different sensors' imaging models (which should account for differences in imaging geometries) - 2D (pixels) or 3D (voxels) registration.
- Automatic realization of the procedure (in order to minimize user induced errors and maximize timely operations, especially when real-time requirements are imposed).





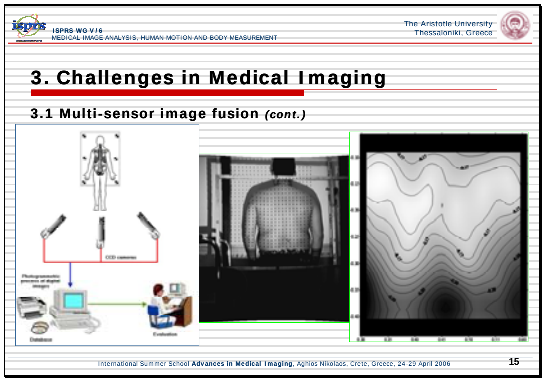
3.1.2. State-of-the art

Image fusion or co-registration can be based either on external targets (either implanted or co-imaged) or on internal fiducials (anatomically recognizable landmarks common in all images). The first case normally provides much better results and external quality measures, but requires implantation or co-imaging of control targets, which is not always possible. Classical examples of the first (implanted) are Börlin (2000) and [URL7, in Appendix A] for use of dental and orthopaedic implants in registration of X-ray images, or the use of titanium screws (Tate and Chapman, 2000) for fusion of MRI and CT spinal images. Examples of the second (co-imaged) are the use of ear rods in X-ray cephalograms (Aoki et al., 2000), (Thomas et al., 1996) for fusion of X-ray and optical images in orthognathic surgery, the use of optical targets (Schewe and Ifert, 2000) for fusion of optical face images with plaster-cast optical image measurements for orthodontic applications, the use of optical targets (Tsioukas et al., 2000), (Zawieska, 2000) for optical image registration for scoliosis treatment or for face reconstruction (Jansa et al., 2000), and the use of optical targets for registration of blood vessels (D'Apuzzo, 2001).

The second case uses highly recognizable standard anatomical landmarks, (e.g. carotid, visual motion area V5 of the brain or the hand section of the rolandic motor area (Turner and Ordidge, 2000)) or solely information generated by the patient's anatomy, which is recognizable in all images. For examples, the reader can refer to (Kiskinis et al., 1998) for fusion of pre-operative DUS (Duplex Ultrasonic Scanning) images with post-operative optical images of specimens of carotid artherosclerotic plaque and post-operative optical microscopic images of dyed plaque slices, to [URL2] for fusion of MRI, PET and SPECT images, to [URL1] for fusion of optical video image with MRI scans for image-guided neurosurgery, and fusion of pre-operative MRI images and intra-operative ultrasound images (Fig. 9).

In both cases, most of the current research efforts are directed more on maximizing qualitative similarities rather than establishing geometric correspondences. The reader may refer to Van den Elsen et al. (1993) for a review of image/volume registration techniques, to Woods et al. (1993), Hill et al. (1994) and Collignon et al. (1995) for description of "similarity" measures and to Wells et al. (1996), Studholme et al. (1996) and Meyer et al. (1997) for registration algorithms maximizing qualitative similarities.

Generally the methods used are based on grey-level information and use either correlation techniques or mutual information minimization. Another suite of techniques is based on surface (or volume) registrations and in most of the cases a previous segmentation is assumed, which, as we will see next, is a serious problem itself. Such techniques, however, very often fail. For example, MRI images suffer from a number of geometric distortions and artefacts up to 4mm (e.g. resonance offsets caused by chemical shifts, "potato-chip" effects, varying slice thickness, "bow-tie" effect, etc., see e.g. (Tate and Chapman, 2000) or [URL3]), which cannot be corrected by the above techniques. Ultrasonic images, from the other hand, are fundamentally "noisy" and "speckled", which presents a major problem in above techniques. Additionally, generally such techniques cannot provide quantitative indications of the registration performance. On the analytical side, the above techniques use merely generic 2D-affine transformations.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The Aristotle University
Thessaloniki, Greece
3. Challenges in Medical Imaging
3.1 Multi-sensor image fusion (cont.)
International Summer School Advances in Medical Imaging, Aghios Nikolaos, Crete, Greece, 24-29 April 2006
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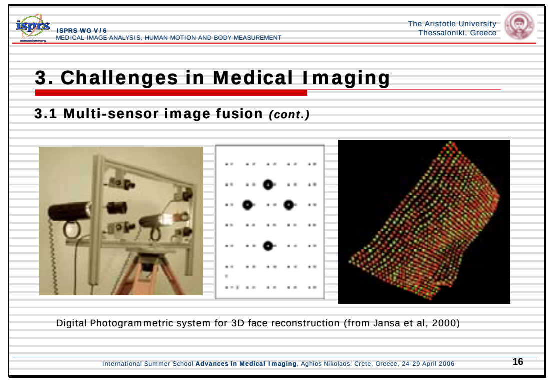
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3. Challenges in Medical Imaging
3.1 Multi-sensor image fusion (cont.)
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International Summer School Advances in Medical Imaging, Aghios Nikolaos, Crete, Greece, 24-29 April 2006
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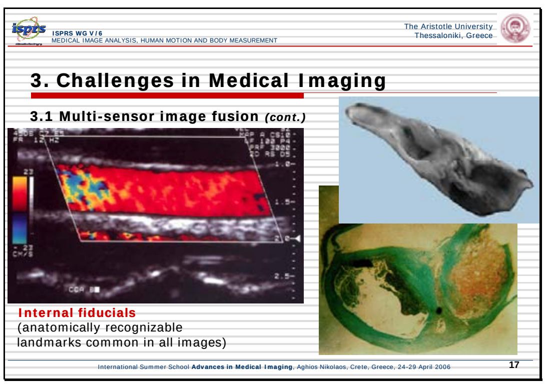
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The Aristotle University
Thessaloniki, Greece
3. Challenges in Medical Imaging
3.1 Multi-sensor image fusion (cont.)
Internal fiducials
(anatomically recognizable
landmarks common in all images)
International Summer School Advances in Medical Imaging, Aghios Nikolaos, Crete, Greece, 24-29 April 2006
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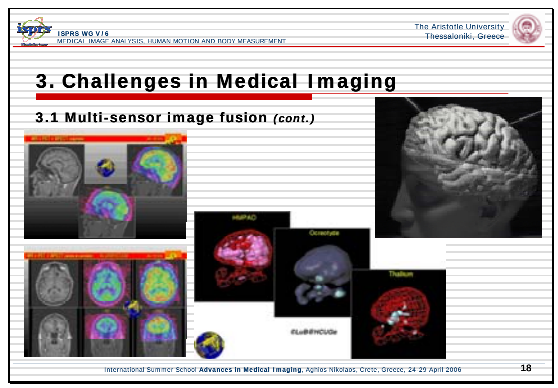
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3. Challenges in Medical Imaging
3.1 Multi-sensor image fusion (cont.)
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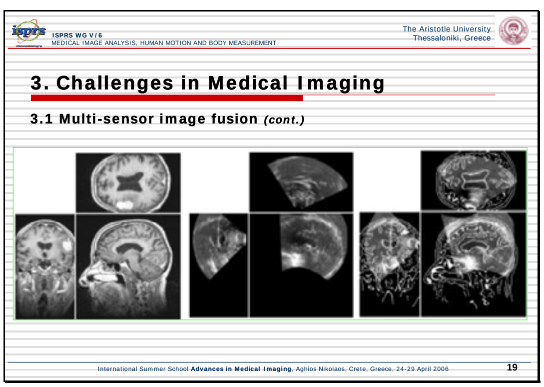
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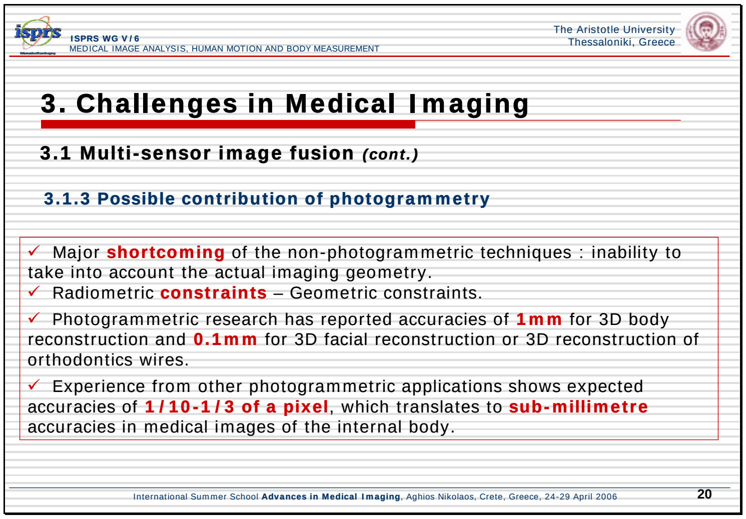


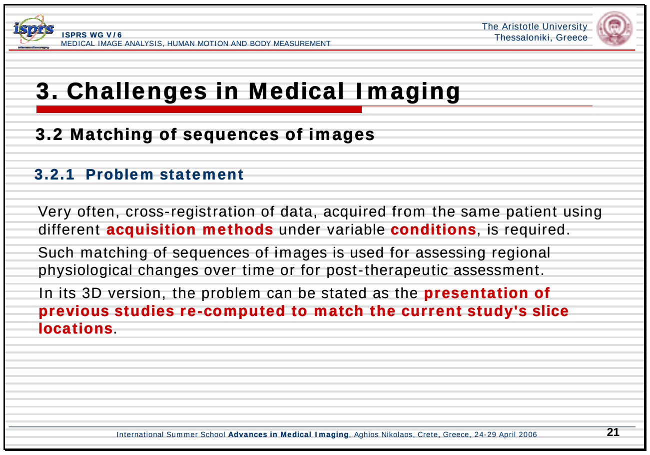
3.1.3. Possible contribution of photogrammetry

The major shortcoming of the non-photogrammetric techniques, developed in image registration, is their inability to take into account the actual imaging geometry; they replace it by a simplistic affine model. Thus, they are left to cope only with the images' similarities in appearance, that is they only impose radiometric constraints, when searching for correspondences. These constraints, however, if strictly imposed, cannot cope with eventual differences in appearances when using different imaging modalities; if loosely imposed they are of little help.

In photogrammetry also, it has been realized, long ago, that mere radiometric constraints are not adequate for achieving high accuracies and high reliability (meaning reduced number of false matches) of results. This is the reason why the quest for geometrical constraints has led to modelling of sensor geometry. In the usual photogrammetric practice, both radiometric and geometric constraints are adjusted together. Additionally, sensor orientation parameters (i.e. imaging angles), which can be rather easily recorded during imaging, can impose additional strict geometric constraints (e.g. epipolar lines), which will highly ease and robustify the matching process, even under poor radiometric similarities. Such sensor models can be easily extended to accommodate for additional sensor imperfections (through self-calibration or test-field calibration procedures) according to usual photogrammetric procedures. It should be also noted that photogrammetry has devised techniques, which can be of local nature and are thus able to produce locally valid matches, despite of possible global dissimilarities.

Photogrammetric research has reported accuracies of 1mm for 3D body reconstruction (e.g. Jansa et al., 2000; Tsioukas et al., 2000) and 0.1mm for 3D facial reconstruction (e.g. Schewe and Ifert, 2000) or 3D reconstruction of orthodontics wires (Suthau et al., 2000). Finally, experience from other photogrammetric applications shows expected accuracies of 1/10-1/3 of a pixel, which translates to sub-millimetre accuracies in medical images of the internal body.

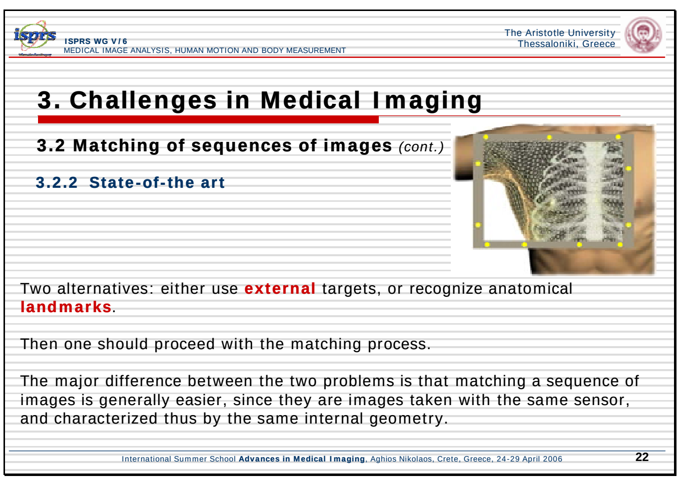
Therefore, this knowledge should be transferred to medical imaging for a better quality of registration. Actually, the situation in many cases is rather easier here, since the necessary sensor models are simpler than the ones routinely used in other photogrammetric applications.



3.2 Matching of sequences of images

3.2.1. Problem statement

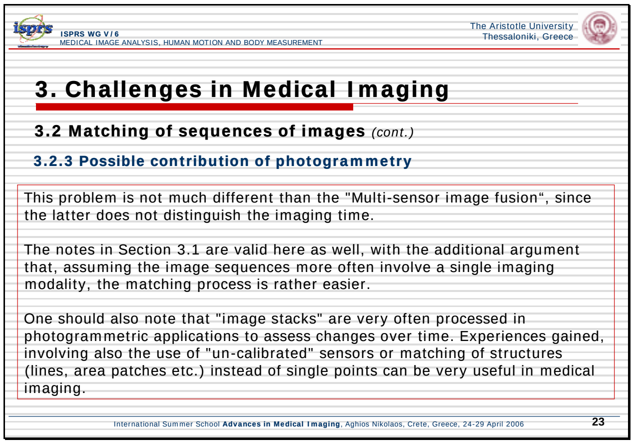
Very often, cross-registration of data, acquired from the same patient using different acquisition methods under variable conditions, is required. Such matching of sequences of images is used for assessing regional physiological changes over time or for post-therapeutic assessment. In its 3D version, the problem can be stated as the presentation of previous studies re-computed to match the current study's slice locations.



3.2.2. State-of-the art

In principle (and in practice) the technical problems involved here are very similar to those mentioned for image fusion. In order to co-register a number of images, again, the alternatives are two: either use external targets, or recognize anatomical landmarks. Then one should proceed with the matching process.

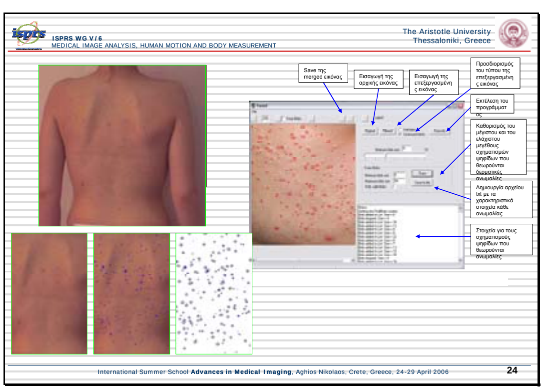
The major difference between the two problems is that matching a sequence of images is generally easier, since they are images taken with the same sensor, and characterized thus by the same internal geometry. This simplifies matching considerably, since more information (and thus external geometric constraints) can be entered into the matching process, making the solution more robust against to mismatches and noise.

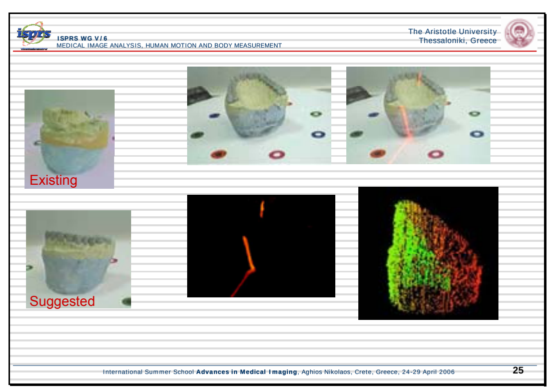


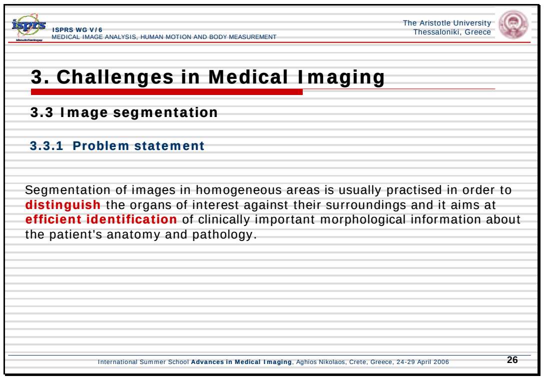
3.2.3. Possible contribution of photogrammetry

On the technical side, this problem is not much different than the "Multi-sensor image fusion" (see Section 3.1), since the latter does not distinguish the imaging time. Therefore the notes in Section 3.1 are valid here as well, with the additional argument that, assuming the image sequences more often involve a single imaging modality, the matching process is rather easier.

One should also note that "image stacks" are very often processed in photogrammetric applications to assess changes over time. These include aerial and satellite imagery, as well as archived photography for e.g. land-use, forest, water resource management, or use of old images for architectural reconstructions. Experiences gained from such applications, involving also the use of "un-calibrated" sensors or matching of structures (lines, area patches etc.) instead of single points can be very useful in medical imaging.



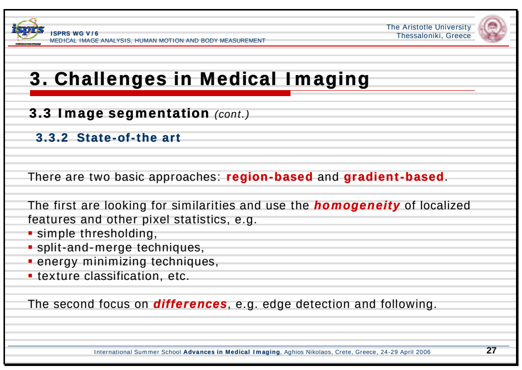


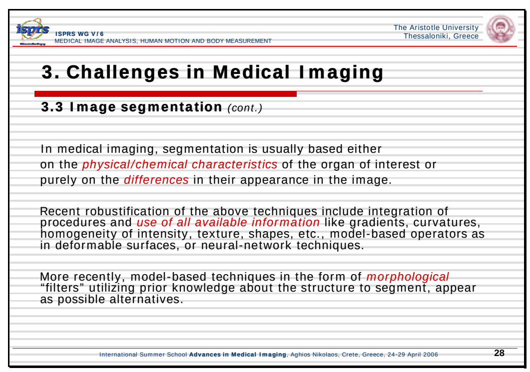


3.3 Image segmentation

3.3.1. Problem statement

Segmentation of images in homogeneous areas is usually practised in order to distinguish the organs of interest against their surroundings and it aims at efficient identification of clinically important morphological information about the patient's anatomy and pathology. In the majority of instances today, a radiologist edits manually an image by enhancing organs of interest or by removing structures that obscure them. This manual editing, besides the time- and workload it requires, is highly depending on the user experience and thus it is non-reproducible; not to mention that without automation, large sequences of images (e.g. in order to get statistically significant results in population studies, or when a large number of organs have to be identified) cannot be processed. Therefore, until now, image segmentation is a major bottleneck in the use of medical image data.

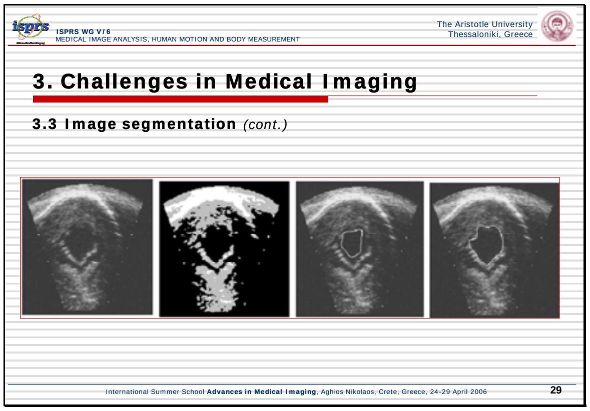


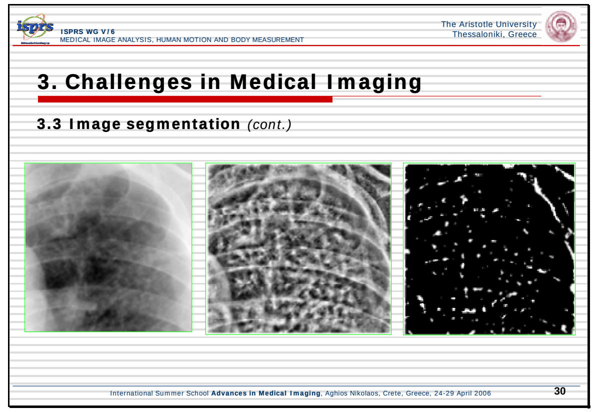


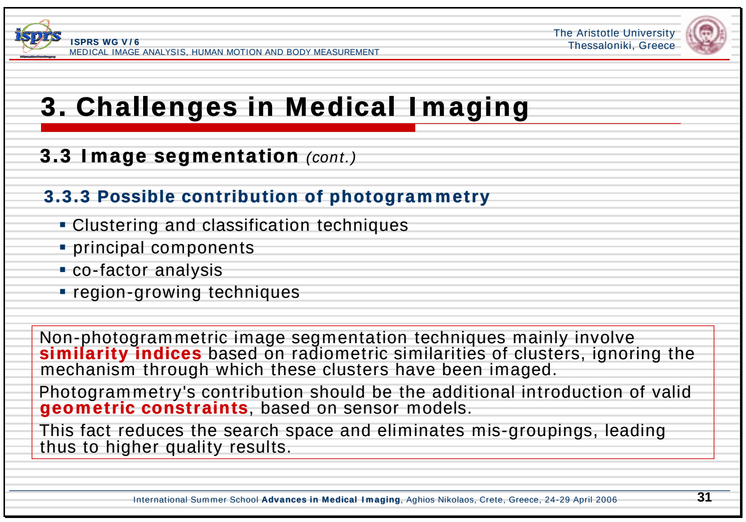
3.3.2. State-of-the art

Medical image segmentation, in principle, is not different from any other image segmentation problem. Image segmentation is one of the primary problems in image processing, and as such it attracted research interest long ago. There is quite an extensive literature on image segmentation, which roughly can be split into two basic approaches: region-based and gradient-based. The first are looking for similarities and use the homogeneity of localized features and other pixel statistics (e.g. simple thresholding, split-and-merge techniques (e.g. (Burt et al., 1981), (Kittler and Illingworth, 1985)), energy minimizing techniques (eg. (Mumford and Shah, 1985)), texture classification etc.) The second focus on differences, e.g. edge detection and following (Canny, 1986; Marr and Hildreth, 1980).

More specifically in medical imaging, segmentation is usually based either on the physical/chemical characteristics of the organ of interest or purely on the differences in their appearance in the image. Recent robustification of the above techniques include integration of procedures (e.g. Chakraborty, 1996) and use of all available information like gradients, curvatures, homogeneity of intensity, texture, shapes, etc., model-based operators as in deformable surfaces (eg. Montagnat et al., 2000), or neural-network techniques (e.g. Kondo et al., 2000). More recently, model-based techniques in the form of morphological "filters" utilizing prior knowledge about the structure to segment, appear as possible alternatives (see e.g. Fig. 10 and Chakraborty, 1996).





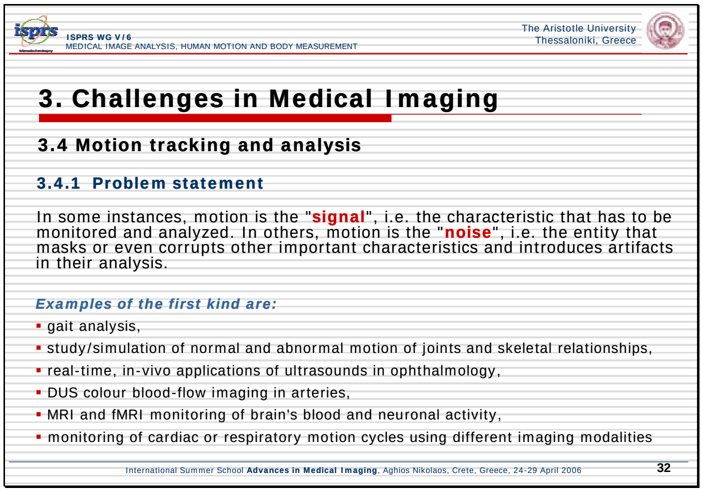


3.3.3. Possible contribution of photogrammetry

Image segmentation, as the generic problem of information extraction from images, was and still is, in one form or the other, a central problem in photogrammetry and remote sensing. Numerous applications call for extraction, aggregation and generalization of the information, which is rather easily and intuitively extracted by the human vision system, while, at the same time, is very difficult to be algorithmically devised and thus automatically processed by machine vision systems.

Due to this necessity, numerous techniques have been developed and tested in photogrammetry, and are successful to various degrees. Clustering and classification techniques of satellite imagery, using principal components or co-factor analysis, and region-growing techniques, for automatic recognition of natural and man-made objects in aerial imagery, belong to this suite.

Again non-photogrammetric image segmentation techniques, in their initial form, involve similarity indices based on radiometric similarities of clusters, ignoring the mechanism through which these clusters have been imaged. Photogrammetry's contribution should be the additional introduction of valid geometric constraints, based on sensor models. This fact reduces the search space and eliminates mis-groupings, leading thus to higher quality results. Additionally, it devised a number of parametric statistical tests and indicators of quality, based on sound statistical principles.



3.4 Motion tracking and analysis

3.4.1. Problem statement

Motion monitoring is very important in many medical instances. In some instances, motion is the "signal", i.e. the characteristic that has to be monitored and analyzed. In others, motion is the "noise", i.e. the entity that masks or even corrupts other important characteristics and introduces artifacts in their analysis. Examples of the first kind are: gait analysis, study/simulation of normal and abnormal motion of joints and skeletal relationships, real-time, in-vivo applications of ultrasounds in ophthalmology, DUS colour blood-flow imaging in arteries, MRI and fMRI monitoring of brain's blood and neuronal activity, monitoring of cardiac or respiratory motion cycles using different imaging modalities, etc. Examples of the second kind are as many and important too: tiny motions of patient during MRI imaging (e.g. head motion of 0.3mm in brain imaging, see e.g. [URL8]) can result in severe diffuse artefacts distributed over the entire image, or completely mask the effect of the used contrasts, tissue movements around large arteries (associated to heart beats) (e.g. 1 mm to 2 mm) or thoracic motions (associated to pressure changes of respiration) cause intensity variations and ghost artefacts in MRI (Turner and Ordidge, 2000), changes in angle between the directions of blood flow and the beam cause important changes to the observed magnitude and direction of blood flow velocity in ultrasonic colour imaging (Wells, 2000), etc.

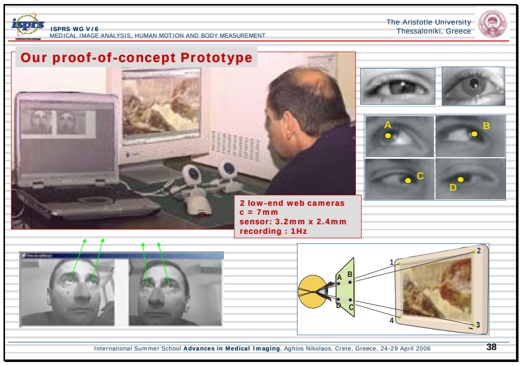
As it is understood, detailed and accurate motion tracking and analysis is very important in all above situations. This involves, depending on the problem at hand, the solution of diverse technical problems, like:

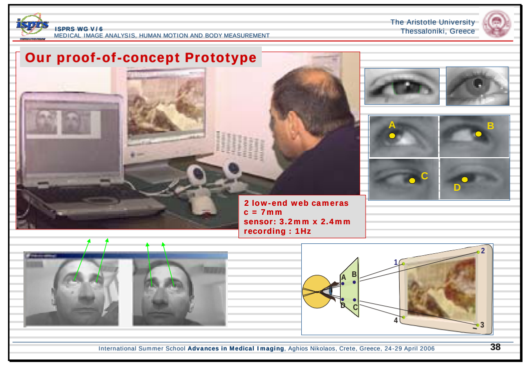
Subject's pose estimation and recovery in an either geometrically controlled (through external fiducials or markers, in cases of outer body measurements) or uncontrolled (in cases of inner body measurements) environments.

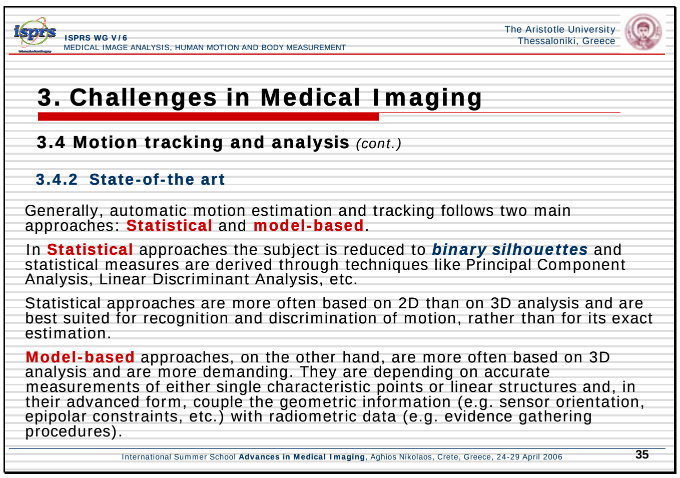
Recovery of multi-view sensors' attitude and position.

Estimation of 3D movement trajectories and recognition of movement patterns.

Automatic realization of the procedure (in order to minimize user induced errors and maximize timely operations, especially when real-time requirements are imposed).







3.4.2. State-of-the art

Generally, automatic motion estimation and tracking follows two main approaches: Statistical and model-based. In the first, typically, the subject is reduced to binary silhouettes and statistical measures are derived through techniques like Principal Component Analysis, Linear Discriminant Analysis, etc. Statistical approaches are more often based on 2D than on 3D analysis and are best suited for recognition and discrimination of motion, rather than for its exact estimation. Model-based approaches, on the other hand, are more often based on 3D analysis and are more demanding. They are depending on accurate measurements of either single characteristic points or linear structures and, in their advanced form, couple the geometric information (e.g. sensor orientation, epipolar constraints, etc.) with radiometric data (e.g. evidence gathering procedures).

To many respects, many of the technical problems involved here are similar to those in image registration or segmentation. Motion tracking in a rigid (e.g. Roche et al., 2000) or non-rigid body fashion (e.g. Chui, 2001 and [URL12] or Zhang, 1992) are among the most popular approaches, very similar to the ones used in matching of free-form curves.

Non-contact motion measurement systems with high-resolution CCD cameras have been developed, which track (infra-red, or red light) either passive retro-reflective or active markers (e.g. Vicon system [URL11], Optotrak and Polaris system [URL9], or the Qualisys system [URL10]). In image-guided surgery, which is one of the most demanding real-time applications, video camera trackable LEDs on the patient (e.g. Leventon (1997), Youmei (1994), [URL4]) have been used to relate real-world object motion to image recognised motion. Additionally, 2D Ultrasonic scanning probes, fitted with positional locators (either electromagnetic or ultrasonic), have been developed for spatially registered 2D scans (e.g. [URL5], [URL6]).


3. Challenges in Medical Imaging
3.4 Motion tracking and analysis (cont.)
3.4.2 State-of-the art (cont.)
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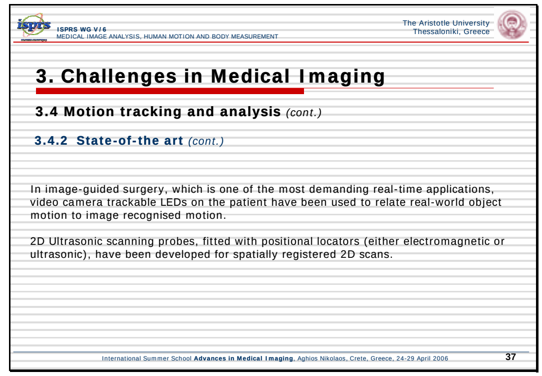
36


3. Challenges in Medical Imaging
3.4 Motion tracking and analysis (cont.)
3.4.2 State-of-the art (cont.)
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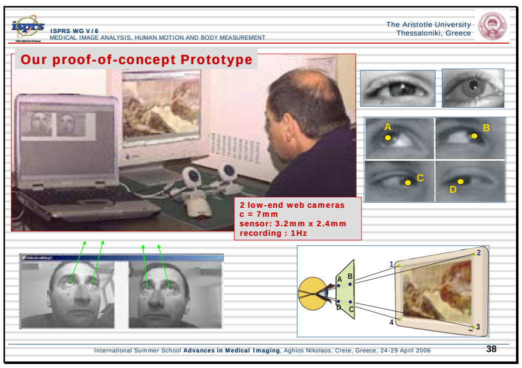
Our proof-of-concept Prototype
A
B
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2 low-end web cameras
c = 7mm
sensor: 3.2mm x 2.4mm
recording : 1Hz
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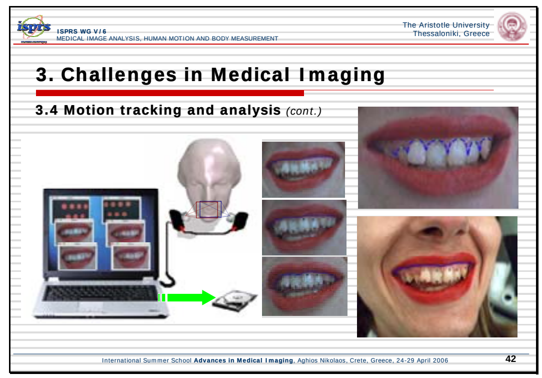
3. Challenges in Medical Imaging
3.4 Motion tracking and analysis (cont.)
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3. Challenges in Medical Imaging
3.4 Motion tracking and analysis (cont.)
3.4.2 State-of-the art (cont.)
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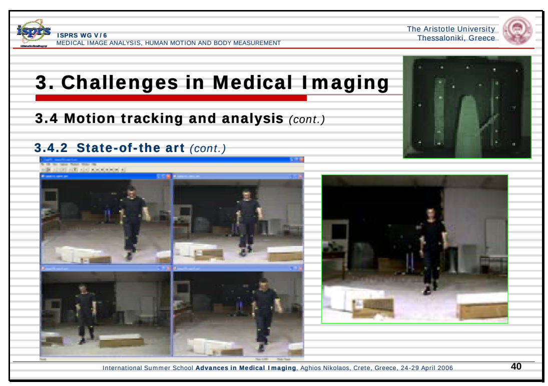
3. Challenges in Medical Imaging
3.4 Motion tracking and analysis (cont.)
3.4.2 State-of-the art (cont.)
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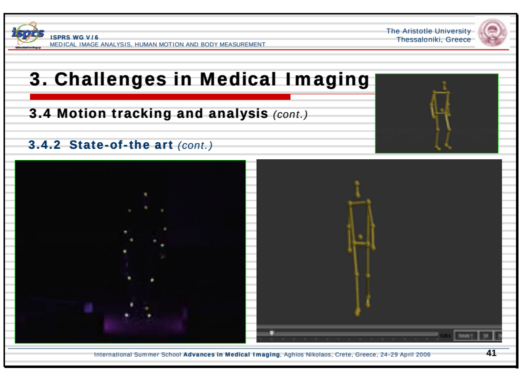
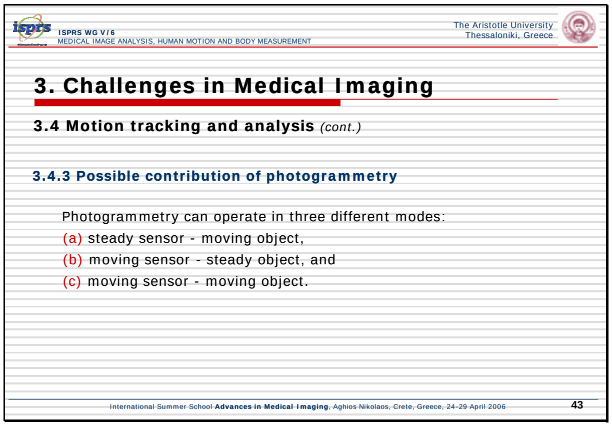

3. Challenges in Medical Imaging
3.4 Motion tracking and analysis (cont.)
3.4.2 State-of-the art (cont.)
41

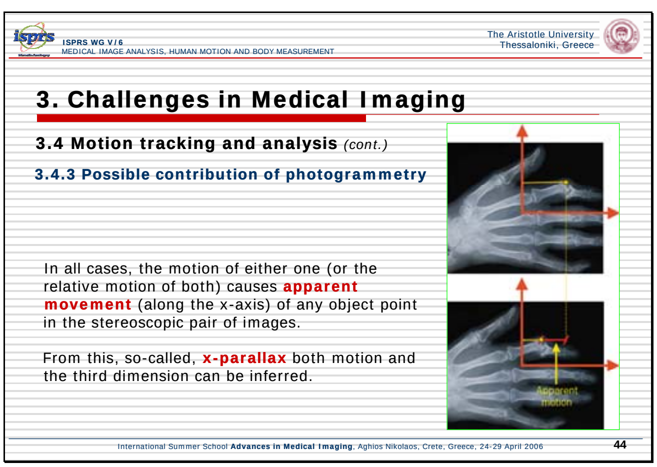


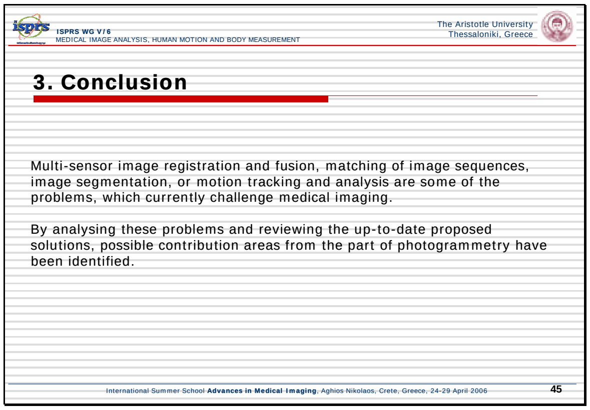
3.4.3. Possible contribution of photogrammetry

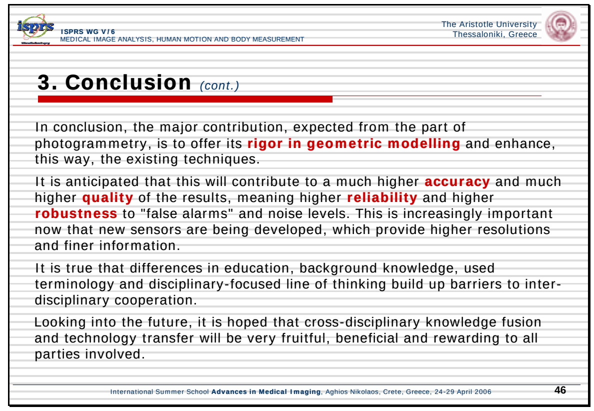
Photogrammetry is principally a 3D positioning technique and it can operate in three different modes: (a) steady sensor - moving object, (b) moving sensor - steady object, and (c) moving sensor - moving object. In all cases, the motion of either one (or the relative motion of both) causes apparent movement (along the x-axis) of any object point in the stereoscopic pair of images (see Fig. 11). From this, so-called, x-parallax both motion and the third dimension can be inferred.

Using this line of thinking, photogrammetry has up to now shown numerous applications with very high quality of results. Besides, the systems mentioned above, and which are based on photogrammetric principles, numerous publications exist (e.g. Anai and Chikatsu (1999), Boulic et al.. (1998), Gravila and Davis (1996), D'Apuzzo et al. (2000), Sharman et al. (2000), Carter and Nixon (2000) to name a few recent ones).

The majority of these applications is based on optical methods and refers to measurements of the exterior body, however. Baring in mind the range of the motion problems, we have already mentioned, we should admit that photogrammetry has not, up to now, used all its resources towards their solution. It is true that the potentiality of the photogrammetric procedures is much higher than what has been realized to date.







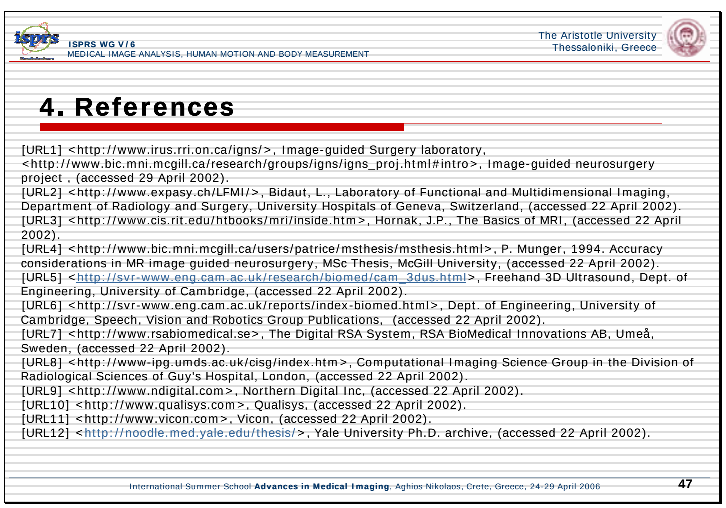
4. Conclusion

Multi-sensor image registration and fusion, matching of image sequences, image segmentation, or motion tracking and analysis are some of the problems, which currently challenge medical imaging. By analysing these problems and reviewing the up-to-date proposed solutions, possible contribution areas from the part of photogrammetry have been identified.

In conclusion, the major contribution, expected from the part of photogrammetry, is to offer its rigor in geometric modelling and enhance, this way, the existing techniques. It is anticipated that this will contribute to a much higher accuracy and much higher quality of the results, meaning higher reliability and higher robustness to "false alarms" and noise levels. This is increasingly important now that new sensors are being developed, which provide higher resolutions and finer information.

It is true that the potential of the photogrammetric procedures is much higher than what has been realized to date. It is also true that differences in education, background knowledge, used terminology and disciplinary-focused line of thinking build up barriers to inter-disciplinary cooperation. And this needs to be changed.

Looking into the future, it is hoped that cross-disciplinary knowledge fusion and technology transfer will be very fruitful, beneficial and rewarding to all parties involved.



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