Lecture Notes in Computational Vision and Biomechanics 23

Guoyan Zheng
Shuo Li *Editors*

Computational Radiology for Orthopaedic Interventions

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Lecture Notes in Computational Vision and Biomechanics

Volume 23

The research related to the analysis of living structures (Biomechanics) has been a source of recent research in several distinct areas of science, for example, Mathematics, Mechanical Engineering, Physics, Informatics, Medicine and Sport. However, for its successful achievement, numerous research topics should be considered, such as image processing and analysis, geometric and numerical modelling, biomechanics, experimental analysis, mechanobiology and enhanced visualization, and their application to real cases must be developed and more investigation is needed. Additionally, enhanced hardware solutions and less invasive devices are demanded.

On the other hand, Image Analysis (Computational Vision) is used for the extraction of high level information from static images or dynamic image sequences. Examples of applications involving image analysis can be the study of motion of structures from image sequences, shape reconstruction from images, and medical diagnosis. As a multidisciplinary area, Computational Vision considers techniques and methods from other disciplines, such as Artificial Intelligence, Signal Processing, Mathematics, Physics and Informatics. Despite the many research projects in this area, more robust and efficient methods of Computational Imaging are still demanded in many application domains in Medicine, and their validation in real scenarios is matter of urgency.

These two important and predominant branches of Science are increasingly considered to be strongly connected and related. Hence, the main goal of the LNCV&B book series consists of the provision of a comprehensive forum for discussion on the current state-of-the-art in these fields by emphasizing their connection. The book series covers (but is not limited to):

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Guoyan Zheng · Shuo Li
Editors

Computational Radiology for Orthopaedic Interventions

Springer

Editors
Guoyan Zheng
Institute for Surgical Technology
and Biomechanics
University of Bern
Bern
Switzerland

Shuo Li
GE Healthcare and University of Western
Ontario
London, ON
Canada

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Preface

Due to technology innovations, the applications of medical imaging in orthopaedic interventions are pervasive, ranging from diagnosis and pre-operative surgical planning, intra-operative guidance and post-operative treatment evaluation and follow-up. The rapid adoption of DICOM standard makes the large image databases readily available in orthopaedics for multi-modal, multi-temporal and multi-subject assessment. Consequently, accurate and (semi-) automatic quantitative image computing is indispensable for various orthopaedic inventions, leading to the creation of a new emerging field called computation radiology. The past two decades have witnessed a rapid development and applications of computational radiology.

Responding to the continued and growing demand for computational radiology, this book provides a cohesive overview of the current technological advances in this emerging field, and their applications in orthopaedic interventions. It discusses the technical and clinical aspects of computational radiology and covers intra-operative imaging and computing for orthopaedic procedures. The book is aimed at both the graduate students embarking at a career in computational radiology, and the practicing researchers or clinicians who need an update of the state of the art in both the principles and practice of this emerging discipline.

Contributed by the leading researchers in the field, this book covers not only the basic computational radiology techniques such as statistical shape modelling, CT/MRI segmentation, augmented reality and micro-CT image processing, but also the applications of these techniques to various orthopaedic interventional tasks. Details about following important state-of-the-art development are featured: 3D pre-operative planning and patient-specific instrumentation for surgical treatment of long-bone deformities, computer-assisted diagnosis and planning of periacetabular osteotomy and femoroacetabular impingement, 2D–3D reconstruction-based planning of total hip arthroplasty, image fusion for computer-assisted bone tumour surgery, intra-operative three-dimensional imaging in fracture treatment, augmented reality-based orthopaedic interventions and education, medical robotics for musculoskeletal surgery, inertial sensor-based cost-effective surgical navigation and computer-assisted hip resurfacing using patient-specific instrument guides.

We sincerely thank our colleagues for their hard work in making their contributions and reviewers for providing timely reviews to us. Special thanks to Ms. Alice Ko who coordinated the long and difficult process of editing and review. Finally, we deeply appreciated the intention of the publisher to make this book possible.

Guoyan Zheng
Shuo Li

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Statistical Shape Modeling of Musculoskeletal Structures and Its Applications

Hans Lamecker and Stefan Zachow

Abstract Statistical shape models (SSM) describe the shape variability contained in a given population. They are able to describe large populations of complex shapes with few degrees of freedom. This makes them a useful tool for a variety of tasks that arise in computer-aided medicine. In this chapter we are going to explain the basic methodology of SSMs and present a variety of examples, where SSMs have been successfully applied.

1 Introduction

The morphology of anatomical structures plays an important role in medicine. Not only does the shape of organs, tissues and bones determine the aesthetic appearance of the human body, but it is also strongly intertwined with its physiology. A prominent example is the musculoskeletal system, where the shape of bones is an integral component in understanding the complex biomechanical behavior of the human body. Such understanding is the key to improving therapeutic approaches, e.g. for treating congenital diseases, traumata, degenerative phenomena like osteoporosis, or cancer.

With the advent of modern imaging systems like X-ray computed-tomography (CT), magnetic resonance imaging (MRI), three-dimensional (3D) ultrasound (US) or 3D photogrammetry a variety of methods is available both for capturing the 3D shape of anatomical structures inside or on the surface of the body. This has opened up the opportunity of more detailed diagnosis, planning as well as intervention on a patient-specific basis. In order to transfer such developments into clinical routine and facilitate access for every patient in a cost-effective way, efficient and reliable methods for processing and analyzing shape data are called for.

H. Lamecker (✉) · S. Zachow
Zuse Institute Berlin (ZIB), Takustr. 7, 14195 Berlin, Germany
e-mail: hans.lamecker@1000shapes.com

H. Lamecker
1000shapes GmbH, Wiesenweg 10, 12247 Berlin, Germany

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In this chapter, we are going to turn the attention on a methodology, which shows great promises for efficient and reliable processing and analysis of 3D shape data in the context of orthopedic applications. We are going to describe the conceptual framework as well as illustrate the potential impact to improving health care with selected examples from different applications.

This chapter is not intended to give an exhaustive overview over the work done in field of statistical shape modeling. Instead, it shall serve as an introduction to the technology and its applications, with the hope that the reader is inspired to convey the presented ideas to his field of work.

2 Statistical Shape Modeling

In this section, the basic conceptual framework of statistical shape modeling is described. There is a large variety of different approaches to many aspects of statistical shape modeling, such as shape representation or comparison techniques, which shall not be covered here. Instead, we are focusing on extracting the essential links and facts in order to understand the power of statistical shape modeling in the context of the applications. The reader interested in more details is referred to [16]. An overview specific to bone anatomy is presented by Sarkalkan et al. [19].

2.1 Representation

3D shape describes the external boundary form (surface) of an object, independent of its location in space. The size of an object hence is part of its shape. For the scope of this chapter, it suffices to know that mathematically, a surface S is represented by a—in general infinite—number of parameters and/or functions x, which describe the embedding of the surface in space, and thus its form. The computerized digital surface representation $S(x)$ in general approximates the shape by reducing the infinite number of parameters x to a finite set. One commonly used representation in computer graphics are triangle meshes, which are point clouds, where the points are connected by triangles, but many other representations like skeletons, splines, etc. are also used.

2.2 Comparison

The fundamental task in analyzing shapes is to compare two shapes S_1 and S_2. This means that for each parameter x_1 for shape S_1 a corresponding parameter x_2 for shape S_2 is identified. One important prerequisite is that such an identification method needs to be independent of the location of the two shapes in 3D space. Such a process is also referred to as matching or registration. For example, for each 3D

Fig. 1 Transformation of a human into a rhinoceros head is made possible through the representation of shapes in a common shape space

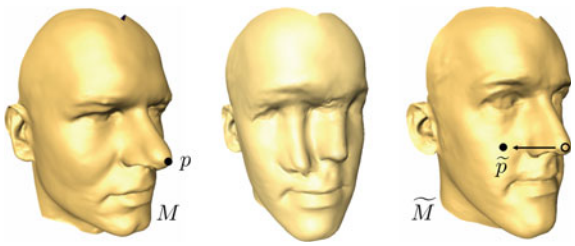

Fig. 2 When the tip of the nose on the *left* head is matched with a point on the cheek on the *right* head, shape interpolation may yield a head with two noses

point on one surface a corresponding 3D point on the other surface may be identified. For other representations, these may not be 3D points but e.g. skeletal parameters, etc. As a consequence one can establish a so-called shape space, where shapes may be treated just like numbers in order to perform calculations on shapes, like e.g. averaging $S_3 = 0.5 \cdot (S_1 + S_2)$ or any other interpolation, see Fig. 1.

Is is obvious that the details of the correspondence identification has a great impact on subsequent analysis, see Fig. 2. Nevertheless, a proper definition for "good" correspondences is difficult to establish in general, and in most cases must be provided in the context of the application. One generic approach to establish correspondence, however, optimizes the resulting statistical shape model built from the correspondences, i.e. its compactness or generalization ability, see Sect. 2.4. Refer to Davies et al. [3] for more details.

2.3 Statistical Analysis

As soon as we are able to perform "shape arithmetic" in a shape space, we can perform any kind of statistical analysis, e.g. like principal component analysis (PCA). This kind of analysis takes as input a set of training shapes $S_1, \ldots, S_n$ and extracts the so-called modes of variations $V_1, \ldots, V_{n-1}$ sorted by their variance in the training set. Together with the mean shape $\overline{S}$ the modes of variations form a statistical shape model (SSM):

$$S(b_1, \ldots, b_{n-1}) = \overline{S} + \sum_{k=1}^{n-1} b_k \cdot V_k \tag{1}$$

The SSM is a family of shapes determined by the parameters $b_1, \ldots, b_{n-1}$, each of which weights one of the modes of variations V_k. For instance, if we set $b_2 = \cdots = b_{n-1} = 0$ and vary only b_1 we will see the effect of the first mode of variation on the deformations of the shapes within the range of the training population. The PCA may be exchanged with other methods, which will alter the interpretation of both the V_k and their weights b_k. See Sect. 3.3.2 for such an alternative approach.

In the PCA case, the idea is that the variance within the training population is contained in only few modes, hence the whole family of shapes can be described with only a few "essential degrees of freedom", see Fig. 3. Note that the shape variations V_i are generally global deformations of the shape, i.e. they vary every point on the shape. Thus, a SSM can be a highly compact representation of a family of complex geometric shapes. Furthermore, it is straightforward to synthesize new shapes by choosing new weights. These may lie within the range of the training shapes or even extrapolate beyond that range.

2.4 Evaluation

With the SSM we can represent any shape as a linear combination of the input shapes or some kind of transformation of those input shapes, e.g. via PCA. However, up to what accuracy can we represent/reconstruct an unknown shape S^* by an SSM $S(b)$? The idea is to compute the best approximation of the SSM to the unknown shape:

$$b^* = \operatorname*{argmin}_b d(S^*, S(b)) \tag{2}$$

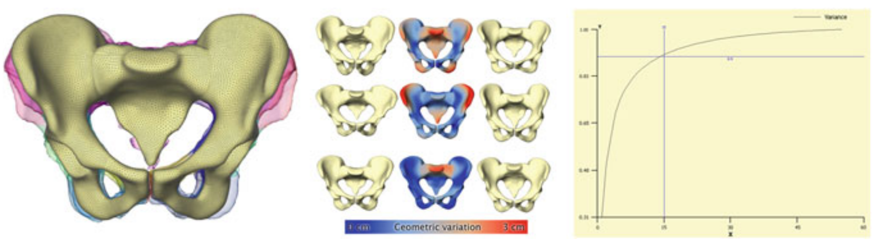

Fig. 3 *Left* Overlay of several training shapes. *Middle* First three modes of variation from *top* to *bottom*. Local deformation strength is color-coded. *Right* 90 % variation lie within 15 shape modes

where $d(\cdot, \cdot)$ is a measure for the distance between two shapes. Then $S(b^*)$ is the best approximation of S^* within the SSM.

If $d(S^*, S(b^*)) = 0$ then the unknown shape is already "contained" in the SSM, otherwise the SSM is not capable of explaining S^*. The smaller $d(S^*, S(b^*))$ for any S^*, the higher the so-called generalizability of the SSM. A better generalizability can be achieved by including more training samples into the model generation process. A good SSM has a high generalizability or reconstruction capability. On the other hand, if $S(b)$ for an arbitrary b is similar to any of the training data sets S_1, …, S_n, the SSM is said to be of high specificity. In other words, synthesized shapes do indeed resemble real members of the training population. Generalizability and specificity need to be verified experimentally.

3 Applications

3.1 Anatomy Reconstruction

One of the basic challenges in processing medical image data is the automation of segmentation or anatomy reconstruction. Due to noise, artifacts, low contrast, partial field-of-view and other measurement-related issues, the automatic delineation and discrimination of specific structures from other structures or the background—seemingly an easy task for the human brain—is still challenging for the computer.

However, over the last two decades, model-based approaches have shown to be effective to tackle this challenge, at least for well-defined application-specific settings. The basis idea is the use a deformable shape template (such as a SSM) and match it to medical image data like CT or MRI. In this case, the shape S^* from Eq. (2) is not known explicitly. Therefore, such an approach—in addition to the SSM—requires a intensity model, that quantifies how well an instance of the SSM fits to the image data, see Fig. 4. From such a model, S^* can be estimated. Many such intensity models have been proposed in the literature. One generic approach is to "learn" such a model from training images similar to the way SSMs are generated [2]. Shape models are also combined with intensity models in SSIMs or shape and appearance Models. An overview can be found in [10].

The strength of this approach is its robustness stemming from the SSM. Only SSM instances can be reconstructed, thus this method can successfully cope with noisy, partial, low-dimensional or sparse image data.

On the other hand, since the SSM is generally limited in its generalization capability, some additional degrees of freedom are often required in order to get a more accurate reconstruction. Here, finding a trade-off between robustness and accuracy remains an issue. One successful approach for achieving such a trade-off are so called omni-directional displacements [13], see Fig. 5.

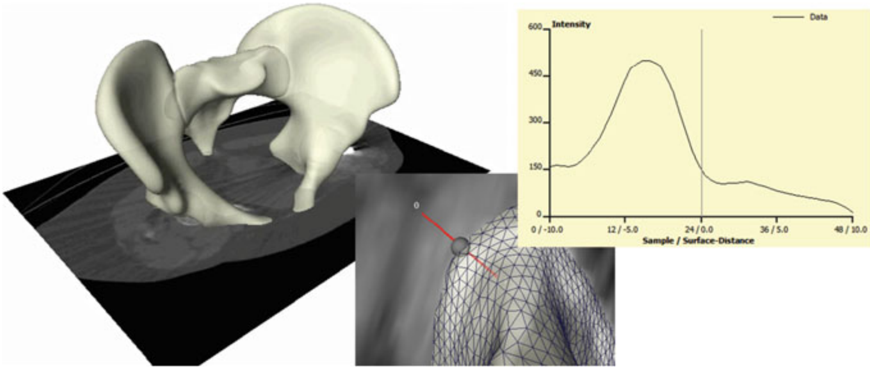

Fig. 4 A SSM is matched to CT data. At each point of the surface an intensity models predicts the desired deformation

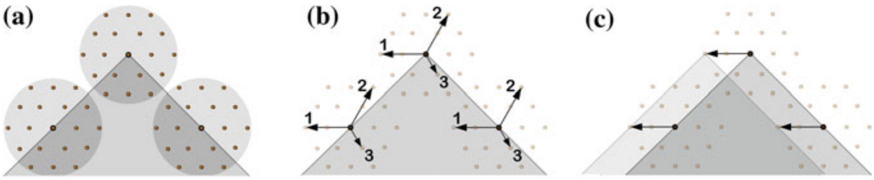

Fig. 5 Instead of just normal displacements as shown in Fig. 4, omnidirectional displacements allow for much more flexibility of local deformations, e.g. in regions of high curvature consistent local translations can be modeled

3.1.1 Example: Knee-Joint Reconstruction from MRI

Osteoarthritis (OA) is a disabling disease affecting more than one third of the population over the age of 60. Monitoring the progression of OA or the response to structure modifying drugs requires exact quantification of the knee cartilage by measuring e.g. the bone interface, the cartilage thickness or the cartilage volume. Manual delineation for detailed assessment of knee bones and cartilage morphology, as it is often performed in clinical routine, is generally irreproducible and labor intensive with reconstruction times up to several hours.

Seim et al. [20] present a method for fully automatic segmentation of the bones and cartilages of the human knee from MRI data. Based on statistical shape models and graph-based optimization, first the femoral and tibial bone surfaces are reconstructed. Starting from the bone surfaces the cartilages are segmented simultaneously with a multi-object technique using prior knowledge on the variation of cartilage thickness.

For evaluation, 40 additional clinical MRI datasets acquired before knee replacement are available. A detailed evaluation is presented in Fig. 7. For tibial and femoral bones the average (AvgD) and the roots mean square (RMS) surface