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Computer Vision-Guided Virtual Craniofacial Surgery

A Graph-Theoretic
and Statistical Perspective

 Springer

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*To my wife Anindita
– Ananda S. Chowdhury*

*To my wife Swati, son Pranav, and
daughter Asha
– Suchendra M. Bhandarkar*

Foreword

An ancient mariner on the open seas had to know where he is before he could navigate to where he had to go. A surgeon, through training and experience, gains a mental image of what that “map” should be. It is called surgical anatomy. This is possible because for the most part, the human anatomy, at the large-scale level (1 cm to 10 cm, for example), is not exceedingly variable. However, to know the precise location of the surgery, dissection is needed to allow either direct visualization or palpation of the particular anatomic structures. Often, such dissection is associated with disruption of normal tissues, interruption of blood supply, prolonging the magnitude of surgery, increasing the risk of potential complications, and lengthening the post-operative convalescence. In recent times, Computer Tomography (CT) and Magnetic Resonance Imaging (MRI) have allowed the surgeon to see this surgical map at a level of detail and precision not previously possible. Recent advances in both scanning instruments and supporting software have transitioned their impact from merely outside the operating room to inside the surgical theater, making intraoperative 3D imaging a reality.

However, most of the existing intraoperative navigation devices are still bulky, time-consuming to use, and increase the potential for contaminating the sterile operative field. Given that the cost per minute in the operating room continues to sky rocket, the more work that can be done before entering the operating room, the more effective and efficient the surgeon can be. This monograph details a collaborative research endeavor over the past five years at the University of Georgia and the Medical College of Georgia in designing a software system that can reconstitute broken bones *in silico*, either through a graphical user interface or in an automated fashion from fracture detection to fracture reduction—a process where the displaced bone fragments are returned to where they should be. The sizes and shapes of the fractured bone(s) and the shape of the *in silico* reconstruction can be obtained and then linked to CAD–CAM devices. Reconstruction plates can then be shaped to fit precisely the individual anatomy, and the optimal lengths, orientations, and locations of the various screws can be determined. Armed with this customized fixation hardware, a surgeon can drastically reduce the time needed in the operating room and, as long as an accurate fiducial transfer is made, achieve an accurate reduc-

tion and fixation of the fractures with significantly less extensive dissection. This approach improves the current state-of-the-art by increasing accuracy, decreasing cost, and reducing both the operative trauma and the risk of operative and postoperative complications to the patient.

As a practicing plastic surgeon, I can recall many times when I wished I had such a software system at my disposal. It was largely on account of this pressing need that we embarked, some six years ago, upon this research endeavor. Having the ability to detect and manipulate the fracture fragments, and return them to their preinjury state *in silico* will allow the surgeons to obtain a more accurate reduction and reconstruction with less extensive dissection. The end result is a much shorter operating time and significantly improved surgical outcome. This monograph is the culminating achievement of the sustained efforts of many people, especially Dr. Ananda Chowdhury, then a Ph.D. candidate at the University of Georgia, and my dear friend, Dr. Suchendra Bhandarkar, Ananda's doctoral research advisor. It is through such collaborative work that we can realize significant, high-impact advances that contribute to the surgical treatment of patients with cranio-maxillofacial fractures.

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Preface

The monograph deals with an important application of computer vision and pattern recognition in the area of medical science, more specifically reconstructive craniofacial surgery. Craniofacial fractures are encountered very frequently in today's fast-paced society; the major causes being gunshot wounds, motor vehicle accidents, and sports-related injuries. Surgical reconstruction is challenging because the surgeons in the operating room have to register the broken bone fragments accurately and under severe time constraints. Within the broad class of craniofacial fractures, the emphasis in this monograph is on mandibular fractures since the mandible is often unprotected and exposed making it especially vulnerable to accidents and injuries. A typical input to a computer vision-based system for virtual craniofacial surgery is a sequence of Computed Tomography (CT) images of a fractured human mandible. The detection of fractures in CT images, the other integral component of reconstructive craniofacial surgery, is often difficult because of the complexity of the fracture patterns, missing data, image intensity inhomogeneities, and presence of noise and undesired artifacts.

A formal treatment of computer vision-guided craniofacial surgery entails the solving of two broad classes of problems, i.e., computer-aided fracture detection and virtual reconstruction, both of which raise several important theoretical and practical issues. From a theoretical standpoint, the monograph discusses several traditional topics in computer vision and pattern recognition such as image registration, image reconstruction, combinatorial pattern matching, and detection of salient points and regions in an image. Several useful algorithms and concepts from two traditionally diverse disciplines, namely, graph theory and statistics are seen to be applicable in this context. The relevant topics from graph theory include maximum-weight graph matching, maximum-cardinality minimum-weight matching for a bipartite graph, maximum-flow minimum-cut determination in a flow graph, and construction of automorphs of a cycle graph. The monograph demonstrates how the above graph-theoretic algorithms can be applied to solve some important problems in computer vision and pattern recognition that pertain to virtual reconstructive craniofacial surgery. The various statistical techniques brought to bear include Markov random fields, hierarchical Bayesian restoration, Gibbs sampling, and Bayesian inference.

We show how these sophisticated statistical methods can solve very important problems in the area of virtual reconstructive craniofacial surgery; problems which are of general interest to the broader computer vision and pattern recognition community as well.

From a practical application-oriented viewpoint, we focus, in this monograph, on a highly relevant biomedical problem, i.e., reconstructive craniofacial surgery. The two integral components of any reconstructive surgery, namely, the detection and localization of fractures, and the subsequent reconstruction from the broken bone fragments, are addressed in depth. The proposed solutions for virtual craniofacial reconstruction and computer-aided fracture detection are aimed principally at increasing significantly the current extent of automation in reconstructive craniofacial surgery. However, the proposed solutions have the inherent potential to tackle similar problems in related fields such as radiology, orthopedic surgery, and histopathology.

The monograph consists of four parts that develop the subject matter in a logically coherent manner. Part I of the monograph contains three chapters which provide a broad overview of the subject and the necessary theoretical foundations. In Chap. 1, we discuss in detail, the overall importance of the proposed work. In Chap. 2, we present some important concepts and algorithms from graph theory, which include graph matching, graph isomorphism, graph automorphism, and network flows. In Chap. 3, we discuss some basic and advanced statistical concepts such as probability, inference, Bayesian statistics, and random fields. Suitable illustrations and examples are used in both Chaps. 2 and 3 to familiarize a general reader with these important concepts. The materials covered in Chaps. 2 and 3 are used extensively in the remainder of the monograph to solve the problems of virtual reconstruction and computer-aided fracture detection.

Part II of the monograph, consisting of Chaps. 4 and 5, is dedicated to virtual craniofacial reconstruction. Chapter 4 is devoted to the different aspects of virtual craniofacial reconstruction in the presence of a single fracture. In this chapter, we discuss various surface matching techniques such as the Iterative Closest Point (ICP) algorithm and the Data Aligned Rigidity Constrained Exhaustive Search (DARCES) algorithm. In addition, we describe how the incorporation of knowledge of bilateral symmetry, biomechanical stability, and suitable modeling of fracture surface irregularity can improve the overall reconstruction accuracy. The Maximum Cardinality Minimum Weight Bipartite Graph Matching algorithm, relevant concepts from Graph Automorphism, Fuzzy set-theoretic modeling, and extraction of mean and Gaussian curvature values from the fracture surfaces are applied at various stages of the reconstruction process. In Chap. 5, the problem of virtual craniofacial reconstruction in the presence of multiple fractures is investigated. This problem is shown to resemble that of assembly of a complex 3D jigsaw puzzle from individual pieces. Thus, the nature of the problem of virtual multifracture reconstruction is shown to be combinatorial in terms of the number of reconstruction options with a worst-case exponential-time algorithmic complexity. In an alternative formulation, this problem is modeled as one of maximum weight graph matching, which has a worst-case polynomial-time algorithmic complexity.

Part III of the monograph consists of three chapters; Chaps. 6, 7, and 8, which focus on the problem of computer-aided fracture detection. In Chap. 6, we present

techniques for detecting surface points on major or well-displaced fractures, which denote situations where the broken bone fragments exhibit noticeable relative displacements. Points of high surface curvature are first detected on potential fracture surfaces in individual CT image slices. A Kalman filter formulation, within a Bayesian inference paradigm, is subsequently used to remove spurious surface points. Chapter 7 discusses the detection of hairline or minor fractures which arise in situations where the broken bone fragments are not visibly out of alignment. A hierarchical Bayesian restoration framework is formulated to detect the hairline fracture and also generate the target pattern which simulates the end result of the bone healing process. We model the fracture as a local stochastic degradation of a hypothetical intact mandible and show how a Markov random field (MRF), incorporated within a hierarchical Bayesian framework, can be used to solve the problem. In Chap. 8, in an alternative formulation, a hairline or minor fracture is modeled as a minimum cut in an appropriately weighted flow network. The classical Ford–Fulkerson algorithm is employed to determine the minimum cut in the aforementioned flow network. Each all of the five chapters on virtual craniofacial reconstruction and computer-aided fracture detection discuss a specific problem and are organized in the following manner:

1. Each chapter starts with a section that introduces and motivates the specific problem.
2. Each chapter discusses the related work for the specific problem and highlights the novelty of the proposed solution.
3. Each chapter presents the theoretical foundations underlying the proposed solution.
4. Each chapter includes a section of experimental results with in-depth analysis.
5. Each chapter contains a conclusion and future work section for the specific problem.

Part IV of the monograph consists of a single chapter. In this final chapter (Chap. 9), we summarize our overall contributions and present a design for a Graphical User Interface (GUI) in which the different methods for virtual craniofacial reconstruction and computer-aided fracture detection are integrated. A section on future research directions is also included. This section, in contrast to the *Conclusions and Future Work* section at the end of each of the Chaps. 4–9 (which focus on a specific problem discussed in that chapter), provides a holistic view of the general directions for future research work in the broader area of computer vision-guided virtual surgery.

The monograph is meant to address a fairly diverse audience including researchers, university faculty, graduate students, and clinical practitioners such as plastic surgeons, orthopedic surgeons, and radiologists. Researchers and graduate students in various diverse disciplines such as computer science, electrical engineering, biomedical engineering, and statistics would find the topics covered in this monograph to be very useful. The formal and elegant modeling of some very general problems in the area of computer vision and pattern recognition by means of graph theory and statistics would be attractive to researchers and graduate students in computer science, computer engineering, and electrical engineering. The monograph

can be used in a one-semester graduate-level course dealing with special topics in computer vision as part of a graduate curriculum in a computer science, computer engineering, or electrical engineering department. Since the monograph presents an elaborate treatise on a relevant biomedical problem, it would be of potential interest to researchers and graduate students in biomedical engineering as well. Researchers and graduate students in statistics with interest in statistical pattern recognition would also find several of the topics, covered in this monograph, very useful. Practicing surgeons in the field of reconstructive craniofacial surgery in particular, and orthopedic surgery in general, and radiologists interested in computer-aided detection of craniofacial fractures in CT scans would also benefit greatly from the research described in the monograph.

We sincerely acknowledge the help and advice of many people in preparing this monograph. We appreciate the strong encouragement of Prof. Sameer Singh and Dr. Sing Bing Kang, the series editors of the “Advances in Computer Vision and Pattern Recognition” monograph series published by Springer. We express our sincere thanks to Dr. Wayne Wheeler, the managing editor for this Springer monograph series, for his useful guidance, and to Mr. Simon Rees and Ms. Catherine Brett for their editorial help. We owe a debt of gratitude to Prof. Robert W. Robinson, Dr. Jack C. Yu, Prof. Gauri S. Datta, Dr. Archan Bhattachraya, Ms. Yarong Tang, Prof. Hamid R. Arabnia, Prof. Ernest W. Tollner, Dr. Edmond Ritter, Dr. Ramon Figueroa, and Prof. Amit Konar for their involvement in the research, described in this monograph, at various stages. Ananda S. Chowdhury was a doctoral student under the supervision of Prof. Suchendra M. Bhandarkar in the Department of Computer Science at the University of Georgia, Athens, Georgia, when the research described in the monograph was carried out. The writing of this monograph began when Dr. Chowdhury was working with Dr. Ronald M. Summers in the Department of Radiology and Imaging Sciences at the National Institutes of Health, Bethesda, Maryland, as a postdoctoral fellow. The monograph was eventually completed after Dr. Chowdhury joined the Department of Electronics and Telecommunication Engineering at Jadavpur University, Kolkata, India, as a faculty member. Dr. Ananda S. Chowdhury deeply appreciates the constant support and encouragement of his parents Dr. Subarna Chowdhury and Prof. Satyabrata Chowdhury, his wife Anindita, and his brother Subha during the course of this research and the writing of the monograph. Prof. Suchendra M. Bhandarkar would like to express his deepest gratitude to his wife Swati, son Pranav, and daughter Asha for their constant encouragement, patience, and understanding during the writing of this monograph. This research work was supported in part by research grants from the Biomedical and Health Sciences Institute (BHSI), Faculty of Engineering (FE), and the University of Georgia Research Foundation (UGARF) at the University of Georgia, Athens, Georgia.

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