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Article

Exploring Fracture Patterns: Assessing Representation Methods for Bone Fracture Simulation

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Abstract: Fracture pattern acquisition and representation in human bones play a crucial role in medical simulation, diagnostics, and treatment planning. This article presents a comprehensive review of methodologies employed in acquiring and representing bone fracture patterns. Several techniques, including segmentation algorithms, curvature analysis, and deep learning-based approaches, are reviewed to determine their effectiveness in accurately identifying fracture zones. Additionally, diverse methods for representing fracture patterns are evaluated. The challenges inherent in detecting accurate fracture zones from medical images, the complexities arising from multifragmentary fractures, and the need to automate fracture reduction processes are elucidated. A detailed analysis of the suitability of each representation method for specific medical applications, such as simulation systems, surgical interventions, and educational purposes, is provided. The study explores insights from a broad spectrum of research articles, encompassing diverse methodologies and perspectives. This review elucidates potential directions for future research and contributes to advancements in comprehending the acquisition and representation of fracture patterns in human bone.

Keywords: bone fracture; fracture pattern; medical simulation; segmentation; image analysis

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1. Introduction

The accurate identification and extraction of fracture patterns in human bones has a key role in the improvement of medical care and the development of advanced medical technologies. The ability to discern and analyze specific bone fracture patterns is essential for healthcare professionals, as it provides crucial information for diagnosis, treatment, and planning of surgical interventions. Furthermore, the automated extraction of these patterns through innovative techniques, such as the use of deep learning algorithms, not only streamlines the process, but also contributes to standardization and accuracy in the interpretation of images by medical trauma professionals.

The population in many countries is aging, so fracture studies are becoming even more relevant. As the population ages, there is a significant increase in cases of bone fractures related to the wear and tear and bone fragility associated with aging [1]. The ability to analyze these fracture patterns in detail becomes essential to better understand the clinical implications and establish good strategies for treatment. A rapid and accurate response to needs contributes directly to the recovery process of patients. At advanced ages, one of the most common cases of fracture is hip fracture, which has a mortality rate of between 5% and 10% in the first month and multiplies over the recovery period [2].

39. Okada, T.; Iwasaki, Y.; Koyama, T.; Sugano, N.; Chen, Y.W.; Yonenobu, K.; Sato, Y. Computer-Assisted Preoperative Planning for Reduction of Proximal Femoral Fracture Using 3-D-CT Data. *IEEE Trans. Biomed. Eng.* **2009**, *56*, 749–759. [CrossRef] [PubMed]
40. Kronman, A.; Joskowicz, L. Automatic bone fracture reduction by fracture contact surface identification and registration. In Proceedings of the 2013 IEEE 10th International Symposium on Biomedical Imaging, San Francisco, CA, USA, 7–11 April 2013. [CrossRef]
41. Buschbaum, J.; Fremd, R.; Pohlemann, T.; Kristen, A. Computer-assisted fracture reduction: A new approach for repositioning femoral fractures and planning reduction paths. *Int. J. Comput. Assist. Radiol. Surg.* **2014**, *10*, 149–159. [CrossRef] [PubMed]
42. Fürnstahl, P.; Székely, G.; Gerber, C.; Hodler, J.; Snedeker, J.G.; Harders, M. Computer assisted reconstruction of complex proximal humerus fractures for preoperative planning. *Med. Image Anal.* **2012**, *16*, 704–720. [CrossRef] [PubMed]
43. Paulano-Godino, F.; Jiménez-Delgado, J.J. Identification of fracture zones and its application in automatic bone fracture reduction. *Comput. Methods Programs Biomed.* **2017**, *141*, 93–104. [CrossRef] [PubMed]
44. Luque-Luque, A.; Jiménez-Pérez, J.R.; Pérez-Cano, F.D.; Jiménez-Delgado, J.J. A compact representation of the bone fracture area. Application to fractured bones of clinical cases. *Comput. Methods Biomech. Biomed. Eng. Imaging Vis.* **2021**, *10*, 476–483. [CrossRef]
45. Luque-Luque, A.; Pérez-Cano, F.D.; Jiménez-Delgado, J.J. Complex fracture reduction by exact identification of the fracture zone. *Med. Image Anal.* **2021**, *72*, 102120. [CrossRef] [PubMed]
46. Zeng, B.; Wang, H.; Xu, J.; Tu, P.; Joskowicz, L.; Chen, X. Two-Stage Structure-Focused Contrastive Learning for Automatic Identification and Localization of Complex Pelvic Fractures. *IEEE Trans. Med. Imaging* **2023**, *42*, 2751–2762. [CrossRef]
47. Yamamoto, N.; Rahman, R.; Yagi, N.; Hayashi, K.; Maruo, A.; Muratsu, H.; Kobashi, S. An automated fracture detection from pelvic CT images with 3-D convolutional neural networks. In Proceedings of the 2020 International Symposium on Community-centric Systems (CcS), Tokyo, Japan, 23–26 September 2020. [CrossRef]
48. Yoon, S.J.; Hyong Kim, T.; Joo, S.B.; Eel Oh, S. Automatic multi-class intertrochanteric femur fracture detection from CT images based on AO/OTA classification using faster R-CNN-BO method. *J. Appl. Biomed.* **2020**, *18*, 97–105. [CrossRef]
49. Yao, L.; Guan, X.; Song, X.; Tan, Y.; Wang, C.; Jin, C.; Chen, M.; Wang, H.; Zhang, M. Rib fracture detection system based on deep learning. *Sci. Rep.* **2021**, *11*, 23513. [CrossRef]
50. Ma, Y.; Luo, Y. Bone fracture detection through the two-stage system of Crack-Sensitive Convolutional Neural Network. *Inform. Med. Unlocked* **2021**, *22*, 100452. [CrossRef]
51. Jia, Y.; Wang, H.; Chen, W.; Wang, Y.; Yang, B. An attention-based cascade R-CNN model for sternum fracture detection in X-ray images. *CAAI Trans. Intell. Technol.* **2022**, *7*, 658–670. [CrossRef]
52. Martinet, A.; Galin, E.; Desbenoit, B.; Akkouche, S. Procedural modeling of cracks and fractures. In Proceedings of the Shape Modeling Applications, Genova, Italy, 7–9 June 2004. [CrossRef]
53. Valette, G.; Prévost, S.; Lucas, L.; Léonard, J. A Dynamic Model of Cracks Development Based on a 3D Discrete Shrinkage Volume Propagation. *Comput. Graph. Forum* **2007**, *27*, 47–62. [CrossRef]
54. Glondu, L.; Muguercia, L.; Marchal, M.; Bosch, C.; Rushmeier, H.; Dumont, G.; Drettakis, G. Example-Based Fractured Appearance. *Comput. Graph. Forum* **2012**, *31*, 1547–1556. [CrossRef]
55. Pérez Cano, F.D.; Luque, A.L.; Jiménez Delgado, J.J. Fracture of geometric bone models. Multiscale simulation issues. *Comput. Methods Biomech. Biomed. Eng. Imaging Vis.* **2021**, *10*, 484–491. [CrossRef]
56. Cohen, H.; Kugel, C.; May, H.; Medlej, B.; Stein, D.; Slon, V.; Hershkovitz, I.; Brosh, T. The impact velocity and bone fracture pattern: Forensic perspective. *Forensic Sci. Int.* **2016**, *266*, 54–62. [CrossRef]
57. Cohen, H.; Kugel, C.; May, H.; Medlej, B.; Stein, D.; Slon, V.; Brosh, T.; Hershkovitz, I. The influence of impact direction and axial loading on the bone fracture pattern. *Forensic Sci. Int.* **2017**, *277*, 197–206. [CrossRef] [PubMed]
58. Jimenez-Delgado, J.J.; Parra-Cabrera, G.; Perez-Cano, F.D.; Luque-Luque, A. Generation and Validation of Osseous Fracture Patterns by Forensic Analysis. *IEEE Access* **2020**, *8*, 211506–211525. [CrossRef]
59. Parra-Cabrera, G.; Pérez-Cano, F.D.; Jiménez-Delgado, J.J. Fracture pattern projection on 3D bone models as support for bone fracture simulations. *Comput. Methods Programs Biomed.* **2022**, *224*, 106980. [CrossRef]
60. Sánchez Montañés, B.; Munill Ferrer, M.; Ruiz Casas, J.; Bescós Atin, M.S. Epignatus: Manejo quirúrgico y multidisciplinar. Un caso clínico. *Rev. Esp. Cir. Oral Y Maxilofac.* **2023**, *44*, 171–175. [CrossRef] [PubMed]
61. Müller, M.; Chentanez, N.; Kim, T.Y. Real time dynamic fracture with volumetric approximate convex decompositions. *ACM Trans. Graph.* **2013**, *32*, 1. [CrossRef]
62. Sekuboyina, A.; Rempfler, M.; Valentinitsch, A.; Loeffler, M.; Kirschke, J.S.; Menze, B.H. Probabilistic Point Cloud Reconstructions for Vertebral Shape Analysis. In Proceedings of Medical Image Computing and Computer Assisted Intervention, Shenzhen, China, 13–17 October 2019; pp. 375–383. [CrossRef]