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Open-Access 3D Bone Shape Databases in Orthopedics: An Unmet Need?

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Abstract

Objective: 3D bone shapes play a critical role in preclinical and clinical orthopedic applications. This study aimed to identify and evaluate 10 most relevant existing online CT databases to see if they meet requirements of biomedical experts.

Method: We performed a systematic search to identify relevant online CT databases for lower extremities. Additionally, a workshop with n=40 biomedical experts was held to gather insights on the benefits, challenges, and users for an online 3D bone shape database. This information was used to establish criteria to evaluate the identified databases.

Results: We found that currently available online databases inadequately address experts' needs, particularly regarding inclusion of different shape formats, such as 3D meshes and CAD models, and inclusion of mechanical properties of bones.

Conclusion: These findings highlight a significant gap between databases' offerings and users' needs, underscoring the need for more comprehensive, accessible resources and advanced tools to support the field's progression.

1 Introduction

3D bone shapes provide morphological and biomechanical information useful for a number of preclinical and clinical applications [1]. They are essential for Statistical Shape Models (SSM), which can capture bone variations within a population [2,3], aiding image segmentation [4–6], 3D reconstruction [7–11], and 2D-3D registration for surgery planning and knee kinematics analysis [12–16]. They have potential for diagnosing disorders, measuring skeletal parameters, and studying injuries [17–22]. Moreover, 3D bone shapes can enable deep learning based surgical planning [23], personalized treatments and implant designs through Finite Element Analysis and Multibody Modelling [24–26]. Furthermore, deep learning based methods can aid surgical planning [23]. Medical education can also benefit from 3D bone shapes [1]. 3D models provide realistic simulations for training medical students and professionals, bridging theoretical knowledge and practical skills [27]. High-quality databases and interactive web applications further enhance orthopedic education [28].

Based on our own work experience, although 3D bone shape data is increasingly being made publicly available, it often turns out that the data needs to be acquired from hospitals' local database. This is due to the fact that the data is often hard to find, limited in the number of bones and databases, covers few information and data formats, and is often motivated by individual questions of the host rather than the needs of the wider orthopedic community. To overcome this situation, in-depth knowledge of orthopedic applications, user requirements and available databases is essential.

Therefore, this paper focuses on two key questions:

1) What CT-based databases are available for lower-extremity bones?
2) How well do these databases meet the specific requirements of biomedical experts?

2 Method

First, we conducted a systematic search on Scopus to identify online lower-extremity (including pelvis) CT databases. The results were reviewed in detail, and only 10 most relevant databases were selected for further analysis.

Second, we gathered n=40 experts from the biomedical field and held a workshop at the University of Twente on 3D bone shape databases. The group was composed of 5 clinicians, 20 engineers, and a variety of other professionals with a biomedical background. The participants were divided into six groups, each with a unique role: Two groups ("fans") were asked to discuss the general applications and benefits, two groups ("critics") focused on identifying the potential barriers, challenges, and risks, and two groups ("users") were tasked with considering the target audience and relevant stakeholders for the database. Each group engaged in a 10-minute discussion on their assigned topic, and at the end of each session, one representative from each group presented the key outcomes. After gathering all the comments, we performed a thematic analysis to identify overarching themes. These themes were further used to establish criteria representing the experts' needs. Finally, the previously identified databases were evaluated based on the criteria.

3 Results

During our search for CT databases, a total of 10 online databases that were most relevant to our study were identified (Table 1; rows). Additionally, experts' comments were categorized in six overarching themes as shown in Figure 1. Based on the identified themes, the criteria for evaluating the databases were established (Table 1; columns). The evaluation results of the previously identified databases based on the criteria are shown in Table 1.

Overall, the results indicate that the identified databases meet only 40% of the experts' requirements. In particular, they are doing well when it comes to including metadata and data acquisition parameters. However, they lack areas like open accessibility, diversity of population, inclusion/exclusion criteria, clinical and pathological assessments, and the inclusion of bone segmentation masks. Also, they are limited in offering 3D meshes, CAD models, and mechanical properties of bones.

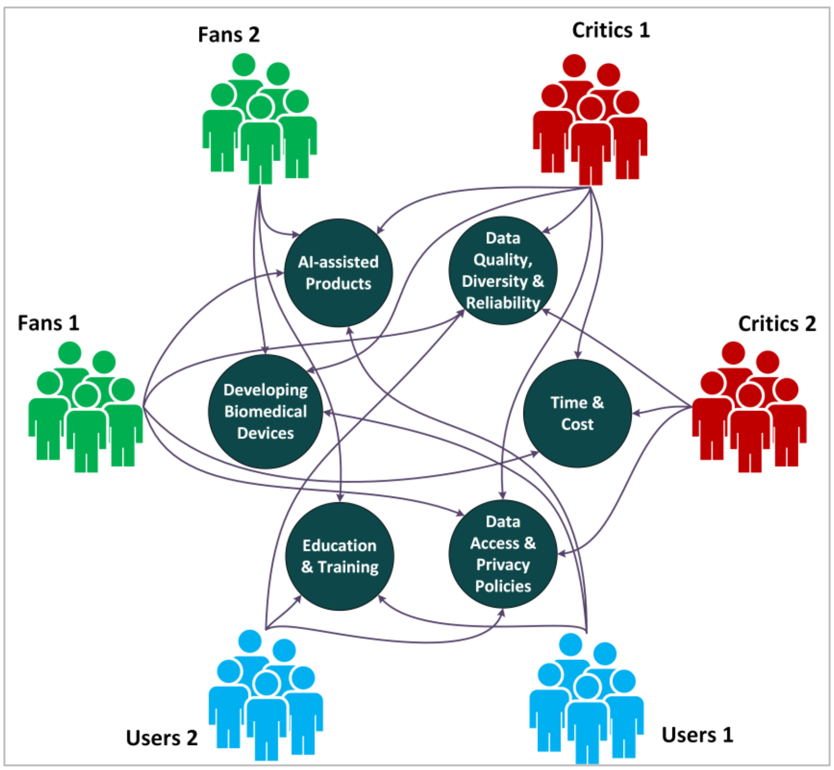

Figure 1: Thematic map illustrating the identified overarching themes based on experts' comments.

Databases	Metadata	Data acquisition parameters	Open-access	Diverse population	Inclusion/ exclusion criteria	Clinical assessment	Bone Segment-ations	3D meshes	CAD models	Mechanical properties	Criteria met (%)
SimTK Tibia-Fibula [29]	✓	✓	✓		✓		✓	✓			**60%**
VSD Full Body Bone Models [30]	✓	✓	✓		✓		✓	✓			**60%**
Kits23 [31]	✓	✓	✓	✓	✓	✓					**60%**
SAROS [32]	✓	✓		✓		✓	✓				**50%**
TCIA FDG-PET/CT [33]	✓	✓		✓	✓	✓					**50%**
NMDID [34]	✓	✓		✓		✓					**40%**
Total Segmen-tator [35]			✓	✓			✓				**30%**
VSD [36]	✓	✓	✓								**30%**
TCIA PELVIC [37]	✓	✓									**20%**
Synapse [38]											**0%**
Criteria fulfilled (%)	**80%**	**80%**	**50%**	**50%**	**40%**	**40%**	**40%**	**20%**	**0%**	**0%**	

Table 1: Evaluation of the lower-extremity (including pelvis) CT databases based on the experts' criteria. Identified databases (rows) are ranked in descending order by the number of criteria they have met, and criteria (columns) are arranged from most to least frequently fulfilled.

4 Discussion

The evaluation of the 10 online databases reveal that they fall short of meeting the needs of experts in the field (Table 1). This discrepancy underscores the need for further development and enhancement of current databases.

A key application of 3D bone shapes in orthopedics is the optimization and evaluation of implant designs within a population, utilizing SSMs of bones [39–43]. To construct these SSMs, 3D bone shapes are indispensable. Despite this necessity, only two of the examined databases provided 3D bone shapes, and these were limited to 3D meshes (e.g., STL) rather than CAD models (e.g., IGES, STEP), which are more suitable for advanced biomechanical design. Additionally, MedShapeNet [44] provides more than 100,000 3D medical meshes including bones and other organs without accompanying imaging data or metadata. While it was excluded from this study due to the absence of image content, MedShapeNet remains useful for generating SSMs directly from 3D meshes.

Open accessibility of databases was a critical gap identified in this study, with only half of the evaluated databases being open access. Providing open-access data is foundational for engaging researchers to develop innovative tools and technologies in orthopedics. For instance, [30] has adopted data from [36] and added segmentation for some subjects, showcasing the benefits of open-access databases in accelerating research and development.

Our study has several limitations that may affect the scope and reliability of the findings. First, we analyzed a small number of databases, which limits the generalizability of our results. Second, the number of experts involved was limited, and their feedback was collected within a short 10-minute window, which may not fully reflect their insights. Third, the study relied only on Scopus for the literature search, potentially missing relevant studies in other sources. Additionally, the research focused solely on CT imaging, and was restricted to the lower extremity, leaving other body regions unexplored.

5 Conclusion

In this study, we examined online bone databases and gathered feedback from experts to understand their needs. We found a clear mismatch between what these databases currently offer and what experts in orthopedics actually require. Comprehensive databases tailored to these needs would greatly benefit both the research and clinical community. Closing this gap is essential for advancing orthopedic research and supporting practical applications in the field. Future research should address the limitations of this study by expanding its scope and depth. These improvements will help produce more comprehensive and generalizable findings.

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