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Toward a Digital Twin for Arthroscopic Knee Surgery: A Systematic Review

ØYSTEIN BJELLAND¹, BISMI RASHEED¹, HANS GEORG SCHAATHUN¹,
MORTEN D. PEDERSEN², MARTIN STEINERT³, ALF INGE HELLEVIK⁴,
AND ROBIN T. BYE¹, (Senior Member, IEEE)

¹Cyber-Physical Systems Laboratory, Department of ICT and Natural Sciences, NTNU-Norwegian University of Science and Technology, 6009 Ålesund, Norway

²Department of Engineering Cybernetics, NTNU-Norwegian University of Science and Technology, 7491 Trondheim, Norway

³Department of Mechanical and Industrial Engineering, NTNU-Norwegian University of Science and Technology, 7491 Trondheim, Norway

⁴Department of Orthopedic Surgery, Ålesund General Hospital, 6017 Ålesund, Norway

Corresponding author: Øystein Bjelland (oystein.bjelland@ntnu.no)

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ABSTRACT The use of digital twins to represent a product or process digitally is trending in many engineering disciplines. This term has also been recently introduced in the medical field. In arthroscopic surgery education, the paradigm shift from apprenticeship to simulation training has driven the need for better simulators, and the current focus is on improving simulators with respect to computational efficiency and system accuracy. However, expanding surgical simulations towards digital twins has not yet been explored. This paper introduces the digital twin concept for arthroscopic surgery, and explores its potential in light of the existing scientific literature. Thus, a systematic review was conducted to summarize and analyze the literature with respect to fast and robust design of an arthroscopic digital twin using patient-specific information, and methods for interactive surgical soft tissue simulation. The review was conducted using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol with three reliable scientific search engines: IEEE Xplore, ScienceDirect and PubMed. Eighty papers were included in the review, and the extracted data included modeling methods, tissue types, constitutive behavior, computational efficiency or accuracy, hardware configuration, haptic device description, software tools, and system architectures. Considering the review, a novel macro-level conceptual arthroscopic digital twin system is presented, and the applicability of the review findings for the identified subsystems are discussed. The proposed system integrates patient-specific images, diagnostic data, intraoperative sensor data, and surgical practice as inputs, and conceptually enables surgical skills training, preoperative planning, and a database of virtual surgeries.

INDEX TERMS Digital twin, biomechanics, haptic rendering, medical simulation, computational modeling.

I. INTRODUCTION

The paradigm shift in surgical education with focus on simulation drives the need for better surgical simulators [1], [2]. In a recent editorial commentary *Arthroscopic Simulators-Are We There Yet?*, Frank [3] highlighted the potential for providing safe surgical training without causing harm to the patient, as well as the importance of evaluating novel simulators with respect to face and construct validity. Moreover, studies have shown that surgery simulation effectively can be used for training of junior resident doctors [4]–[6]. A review

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by Morgan *et al.* [7] identified 23 virtual reality-based knee arthroscopy simulators, where 14 were developed by academic institutions. These simulators typically include a virtual reality display, haptic feedback, real-time interactive simulation and standardized operation-specific training procedures. Another article by Vaughan *et al.* [8] reviewed nine virtual reality-based arthroscopic knee simulators, and pointed to patient-specific surgery simulators as an important future development as surgeons can practice specific procedures before an in-vivo procedure. Later, Ryu *et al.* [9] reviewed medical literature for the educational value of patient-specific simulation, and commented that current simulators provide limited educational value for senior surgeons.

They concluded that if the technology is developed further, patient-specific simulators could have the ability to develop higher-level competencies outside a clinical setting.

The introduction of new technology in surgery also influences other aspects of lifelong arthroscopic surgical education. Surgical tools with novel sensors have the potential to provide more information about surgical procedures. Tool-position systems can be used to improve surgeon performance by providing an accurate display of the tool position relative to the patient's anatomy. Force sensors and estimation methods can provide valuable real-time assistance to limit potentially injuring the patient. Golahmadi *et al.* [10] investigated tool-tissue interaction forces in surgery, and highlighted how “force measurement can provide a quantitative metric of surgical skills, potentially useful for surgical training and assessment.” They found that in general, expert surgeons tended to use less force than novice and intermediate surgeons.

With more patient and surgical data available, the emergence of machine learning and artificial intelligence has the potential to provide new insights into surgical procedures. In a review of the history of computer-assisted orthopedic surgery (CAOS), Picard *et al.* [11] stated that CAOS is still at the stage of “measuring data” without really knowing what the best use of these data is. Recently, Anh *et al.* [12] compared feature extraction techniques for surgical skill assessment, and found that a convolutional neural network (CNN), which is a deep learning method, significantly outperformed other techniques. These advancements pave the way for a novel concept for arthroscopic surgery simulation, namely, the digital twin.

With a background in systems engineering, Grieves [13] first coined the term digital twin as

(...) a set of virtual information constructs that fully describes a potential or actual physical manufactured product from the micro atomic level to the macro geometrical level. At its optimum, any information that could be obtained from inspecting a physical manufactured product can be obtained from its Digital Twin.

Working towards real-time interactive surgical simulation, Lauzeral *et al.* [14] adopted the term and stated that “(...) the Digital Twin, merges complex biophysical modeling and advanced real-time simulation techniques with data assimilation and analysis for decision support”. Later, Fuller *et al.* [15] pointed to the use of digital twins for planning and performing surgical procedures as a promising application. Corral-Acero *et al.* [16] introduced the digital twin concept in cardiology by stating that “providing therapies that are tailored to each patient, and that maximize the efficacy and efficiency of our healthcare system is the broad goal of precision medicine”. They highlighted that mechanistic and statistical models are the two pillars of the digital twin. In 2021, Chase *et al.* [17] introduced the digital twin concept for intensive care and transferred the definition

from manufacturing to clinical practice. They stated that “In medicine, the physical system is the patient, or a particular organ or physiological system to be managed”. Later, in orthopedics, Aubert *et al.* [18] used the term digital twin to describe a patient-specific finite element model of a tibial plateau fracture for optimizing trauma surgery and postoperative management. Similarly, Hernigou *et al.* [19] used the term to describe the identification of a personalized motion axis of the tibiotalar joint in total ankle arthroplasty. They defined a digital twin as “(...) a near real-time digital image of a physical human”.

As a logical evolution and novel contribution, we introduce the digital twin concept in the context of arthroscopic surgery, and explore its potential in light of the existing scientific literature. We argue that a true digital twin expands on previous surgery simulators by including not only generic anatomical models, but patient-specific digital information with real-time calibration of simulations using intraoperative data. Inspired by previous efforts, we define an arthroscopic digital twin as *virtual information that fully describes a patient-specific biomechanical system, such as a joint*. Utilizing digital twins, we see the potential for creating a database of surgical procedures with known outcomes that can be used for (i) training resident doctors and (ii) preparation for experienced surgeons before an advanced procedure. In its optimum form, the digital twin could serve as a virtual environment where novel arthroscopic surgical procedures can be explored, and new ones can be designed. To do so, we argue that the digital twin needs to simulate all biomechanical behaviors of the joint so that it is not restricted to individual tissue types. Existing simulator systems largely rely on a given set of instructions or sequences that must be performed in a specific order. We argue that a digital twin should not be constrained to such sequences, but rather allow the surgeon to be free to perform any procedure and observe the implications on the digital twin. These implications could include joint stability and range of motion during surgery. We limit the scope of this paper to consider a digital twin of the knee. As orthopedic health service is highly specialized, we argue that limiting the digital twin to a specific joint is best suited for clinical practice. Similarly, we consider the lifecycle to be the lifecycle of a given treatment, starting with preliminary investigation and diagnosis, through surgery and treatment, and proceeding through recovery and rehabilitation.

The contribution of this paper is twofold, as it (i) reviews current state-of-the-art of enabling technologies needed for realization of a digital twin for arthroscopic surgery, and (ii) presents a novel macro-level conceptual digital twin system. The review investigates the literature from January 2018 to December 2021 to cover gaps from previous reviews and has the following objectives:

- Investigate fast and robust design of an arthroscopic digital twin using patient specific information.
- Explore methods for interactive surgical soft-tissue simulation for a digital twin, emphasizing speed and accuracy.

The remainder of this paper is organized as follows. Section II presents relevant user scenarios that drive the development of digital twins and shows their potential value in clinical practice. Section III explains the methods used for conducting the literature review following the PRISMA protocol. The results of the literature review are presented in Section IV. Section V presents a novel conceptual macro-level system of a digital twin for arthroscopic surgery, and discusses the applicability of the findings from Section IV in the identified subsystems. Section VI discusses the methods used, ethical considerations, and suitability of a digital twin in clinical practice.

II. USER SCENARIOS

Based on discussions with orthopedic surgeons specialized in arthroscopic surgery at Ålesund General Hospital, considering how they conceive a digital twin relevant for knee arthroscopy, we have identified three relevant user scenarios:

- Resident doctor with little surgical experience.
- Specialist surgeon facing a difficult surgery on a specific patient.
- Specialist surgeon with limited access to practicing certain types of surgery, and for rare cases.

The first scenario concerns resident doctors specializing in arthroscopy. A lower volume of some arthroscopic surgeries, such as partial meniscectomies, combined with a higher demand for specialized competence, has led to a gap in training subjects for the skills needed to transition from student to specialist. Surgery simulation can fill this gap by supplying a generic kinematic anatomical model with haptic feedback for certain types of surgeries, allowing for high-volume training. Several existing generic commercial-(Symbionix ArthroMentor, Simendo arthroscopy simulator, Virtamed ArthroS) and academically developed arthroscopic surgery simulators [20]–[24] supply this functionality. However, both Vaughn *et al.* [8] and Frank [3] pointed out that validation evidence of effectiveness with respect to transfer, face, and skill validity is missing in the literature.

The second scenario involves specialist orthopedic surgeons facing a challenging case of a specific, and sometimes rare surgery. Preoperative planning using a digital twin of a specific patient, including exact patient-specific 3D anatomy, realistic material properties and haptic feedback, could potentially (i) increase the surgeon's confidence, (ii) reduce the risk of unknown challenges, and (iii) lead to fewer intraoperative complications. To attain these potential benefits, the process of establishing the digital twin of the injured patient must be sufficiently fast to enable the surgeon to practice before surgery. For arthroscopic knee surgeries, this is considered mostly relevant for non-critical procedures; therefore, the time span normally ranges from a few days to a few weeks.

The third scenario provides access to a bank of special surgical cases. Surgeons working in smaller hospitals generally have a lower volume of special cases. To prepare surgeons for

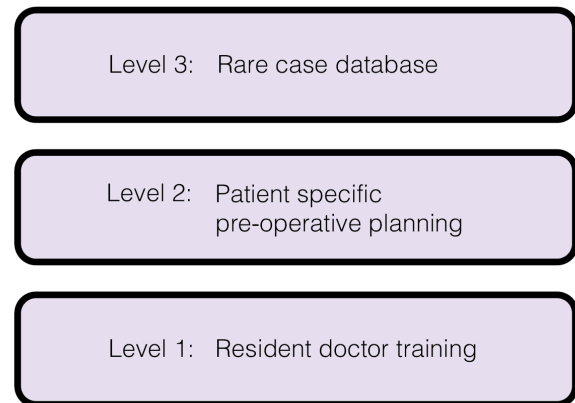


FIGURE 1. Three levels of use cases for a knee-arthroscopic digital twin.

these cases, as some will ultimately encounter them, a digital twin will enable the sharing of patient specific surgical cases. At a minimum, this requires the sharing of patient-specific anatomy and biomechanical properties. However, to significantly improve the value added from such a system, live tool-tissue interaction data, supplemented by other sensor data and operational statistics, could be added.

III. METHOD

Recent literature reviews on soft tissue simulation [25], surgery simulation [7], [8], and haptic feedback [4], [26], [27] provide a good overview of relevant enabling technologies for real-time surgery simulation systems up until 2018. Therefore, we conducted a systematic literature review in the time period from January 2018 to December 2021 following the PRISMA protocol [28]. The purpose of this review was to identify relevant enabling technologies for a digital twin for arthroscopic knee surgery, and the search was therefore directed towards technical articles.

Because the review was limited to the period 2018–2021, and because surgical simulation is a highly interdisciplinary field, we have cited studies prior to this time period to introduce important concepts in the respective sections. This is to give the reader a better understanding of the presented methods and form a more complete image of the digital twin system. However, we emphasize that when review results are displayed explicitly in tables, only the review results are presented.

The search was performed using three scientific databases: IEEE Xplore, ScienceDirect, and PubMed. Six search terms were adopted from Nguyen *et al.* [25] to investigate the latest developments in soft tissue deformation, and two additional search terms were added to investigate digital twins and haptic feedback. The search terms are listed in Table 1.

Two independent reviewers screened and selected search results. The articles were selected from the respective databases based on title and their relevance to one or more of the following categories: *digital twins*, *patient-specific*

imaging, material modeling, simulation strategies, haptic feedback, surgical data collection, and system architecture. No automation tools were used. After the initial selection, the articles were grouped into one of the respective categories and added to a database. The two reviewers then worked together to assess whether the articles met the inclusion criteria, and another selection round was performed based on abstract. Grouping and further selection decisions were made by consensus between the two reviewers. Following this, a full-text assessment was made to decide on the studies to be included in the review.

Papers describing technical development of a digital twin for arthroscopic surgery have been included. Specifically, the inclusion criteria were papers describing soft tissue behavior, the development of surgical simulations, haptic device or software development, digital twins in medicine, and intraoperative sensors for orthopedic surgery. Papers describing simulation strategies that only applied to primitive geometry, and papers focusing on virtual reality (VR) or augmented reality (AR) with head-mounted displays have been excluded. Journal articles and conference papers were included, but book chapters, encyclopedia articles and letters were excluded.

The initial search resulted in a total of 103,325 articles, with a distribution of 98,835 articles from ScienceDirect, 3,203 articles from PubMed and 1,287 articles from IEEE Xplore. From ScienceDirect, search term #5 resulted in a total of 65,205 results alone, with 27,969 articles from the time period 2018-2019 and 37,236 articles from 2020-2021. Here, the first 6000 articles in the time period 2018-2019 and the first 6000 articles from 2020-2021 were checked, reducing the total number of articles to 50,120. The 50,120 articles were then screened based on title, and 49,857 articles were excluded. A total of 263 articles were then sought for retrieval based on their title, of which 53 were duplicates. A total of 210 articles were assessed based on the abstract. From here, 99 articles were assessed for eligibility based on their full text. Finally, 80 studies were included in the review. The selection process is illustrated in Fig. 2.

An independent reviewer reviewed each article. Where necessary, discussions were held between the two reviewers. The data extracted from the results included: *modeling methods, tissue types, constitutive behavior, computational efficiency or accuracy, hardware configuration, haptic device description, software tools and system architectures.*

IV. REVIEW

A. PATIENT SPECIFIC IMAGING

Patient-specific three-dimensional physiological images form the basis of a digital twin. Four studies were selected for inclusion in this review. Three-dimensional medical imaging modalities include 3D-ultrasound, computer tomography (CT), positron emission tomography (PET), and magnetic resonance imaging (MRI). In addition, handheld computer vision-based 3D-scanning techniques have

recently emerged [29]. Each imaging modality has its strengths and weaknesses in different applications. CT and MRI are relevant for arthroscopic surgery planning and simulation because of their ability to recreate internal bone structures [30]. A high-resolution image of a human knee takes approximately 45 minutes with MRI, and 30 minutes with CT. However, MRI performs better in terms of recreating soft structures such as cartilage, tendons and ligaments.

Three-dimensional medical imaging data formats include Analyze, Minc, Digital Imaging and Communications in Medicine (DICOM), and Neuroimaging Informatics Technology Initiative (Nifti) [31]. For MRI, the quality of the 3D-model is dependent on the image slice thickness, as well as sequence parameters such as T1-, T2-, PD-, or FS-weighted sequences. To distinguish between different anatomy in the 3D-reconstruction of an MRI image, segmentation must be performed. Three approaches for automatic MRI segmentation are model-based, image-based and hybrid methods. Model-based methods are methods in which landmark positions are determined by minimizing an energy function. Image-based methods are based on the labelling of voxels, and is also known as dense-segmentation. Examples include level set, graph cut and fully convolutional networks [32]. Recent advances in automatic segmentation using convolutional neural networks have reduced the segmentation times of MRI images from several days to a few minutes. For example, Sun *et al.* [33] successfully automatically segmented 12 different structures in a healthy knee in a few minutes.

After segmentation, a three dimensional mesh can be generated using a 3D-reconstruction algorithm such as marching cubes [34] or dual contouring [35]. This produce a polygonal mesh that approximate the surface of the geometry. Following this, meshing methods, such as Delaunay tetrahedralization can be used to create a three-dimensional volumetric mesh. Recently, Cheng *et al.* [36] presented a framework for improved computational performance and vision effect of 3D-point cloud reconstruction for medical images.

Some medical imaging modalities also have the potential to provide an estimation of in vivo biomechanical properties. Magnetic resonance elastography (MRE) obtains information regarding tissue stiffness by studying the propagation of mechanical waves through the tissue using MRI [37]. Shear-wave elastography (SWE) is another imaging modality for estimating tissue stiffness based on ultrasound. Kuervers *et al.* [38] recently studied the effects of knee angle and quadriceps force on SWE measurements of the patellar tendon. They concluded that SWE is a promising and reliable method for measuring the tendon stiffness. Further, the mapping of material properties from voxels to a model finite element model is another way to formulate constitutive behavior. The data obtained from a CT scan are in Hounsfield units (HU), which vary according to the physical density of the tissue. Toniolo *et al.* [39] developed an almost

TABLE 1. The search terms used for the review process.

#	Search terminologies (terms)	Search terms (STs)
1	Computer-aided medical simulations/systems	Real-time AND computer-aided AND medical AND(simulations OR systems)
2	Real-time medical simulations	Real-time AND medical AND simulations
3	Real-time muscle deformation models	Real-time AND muscle AND deformation AND models
4	Real-time orthopaedic/orthopedic surgery	Real-time AND (orthopaedic OR orthopedic) surgery
5	Real-time finite element methods	Real-time AND finite AND element AND methods
6	Real-time soft-tissue deformations	Real-time AND soft AND tissue AND deformations
7	Digital twin orthopedic surgery simulations	Digital AND twin AND (orthopedic OR orthopaedic) AND surgery
8	Haptic feedback real-time orthopedic surgery	Haptic AND feedback AND real-time AND (orthopedic OR orthopaedic) AND surgery

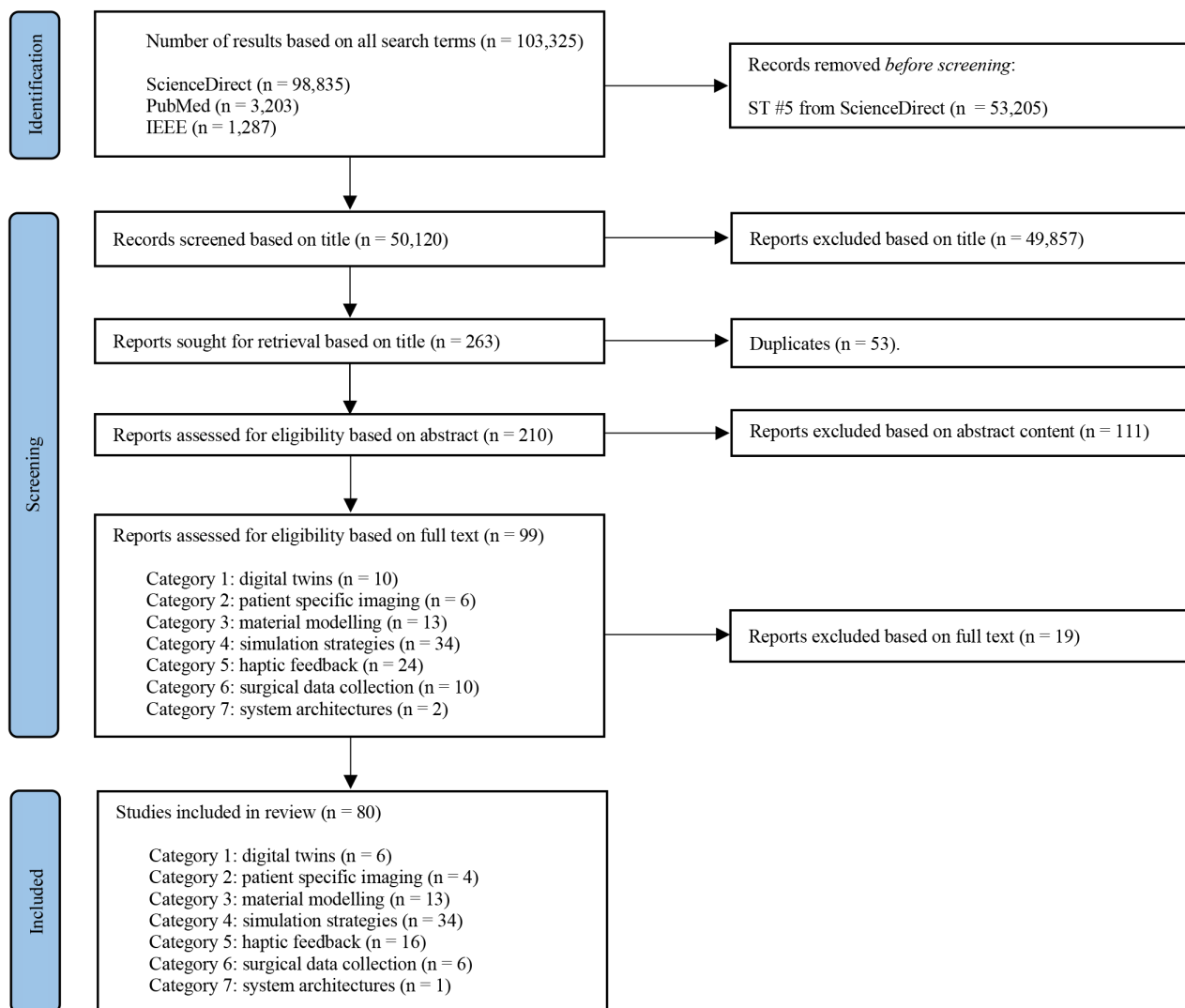


FIGURE 2. Workflow of selection process using PRISMA protocol.

automatic procedure to predict orthotropic elastic constants by analyzing the local HU value, and identified the anisotropic directions considering the HU value distribution around the specific location.

B. REAL-TIME INTRAOPERATIVE DATA COLLECTION AND SYSTEM IDENTIFICATION

Novel sensors are making their way into operating theatres in the setting of robot-assisted surgery and for

technology-assisted manual surgery to improve surgeon performance. Sensor technologies can be classified as tool-position estimation for surgical navigation and force sensing. From the review, six papers describing intraoperative data collection were included.

In combination with AR and VR support systems, tool-position systems have the potential to improve surgeon performance by providing an accurate display of the tool position relative to the patient's anatomy. Ma *et al.* [40] used the sensor fusion of stereo vision and surgical instrument Inertial Measurement Unit (IMU) data for virtual rendering and self-position tracking in knee arthroscopy, as shown in Fig. 3. Hu *et al.* [41] demonstrated markerless navigation using a RealSense D415 camera and bounded iterative closest point (BICP) method for femoral drilling. Jonmohamadi *et al.* [42] demonstrated the automatic segmentation of multiple structures from arthroscopy videos during surgery. Chen *et al.* [43] demonstrated a tissue property-based model deformation method for updating the 3D preoperative tissue structure in accordance with the actual intraoperative arthroscopic view. They used intraoperative arthroscopic images to capture 3D-anatomical locations, together with preoperative CT images to capture patient anatomy, and an optical tracking system to track arthroscopy. The tool position and live-tissue deformation were displayed using an AR overlay on a glasses-free AR device. The mean error between the virtual and real arthroscopic images was 0.32 mm.

Tool-force sensing systems can be classified into direct and indirect methods. In direct methods, the force/torque sensor is placed near the patient or tissue, usually in the tool. Sensor examples include strain gauges, microelectric mechanical systems (MEMS), piezoelectric, optical, and Bragg sensors [44]. In a recent review, Nazari *et al.* [45] highlighted that image-based force estimation techniques are feasible for providing haptic force feedback in medical telerobotic systems. They further noted that haptic information could be indirectly extracted through force estimation by employing a mathematical model for soft tissue, considered a deformable object, and visual feedback provided by a vision system placed in the operating room. They highlighted learning-based methods as a highly trending approach for modeling deformable objects. Here, an artificial intelligence (AI) model estimates the object model by learning a relationship between the applied forces and object deformations. The reader is referred to their review for technical details concerning image processing techniques, and image-based force estimation systems.

C. MATERIAL MODELING

The two categories of tissues that must be addressed when designing an arthroscopic digital twin are soft- and hard tissues. Blood vessels, nerves, tendons, and tissues surrounding bones and joints are examples of soft tissues, whereas cortical and medullary bones are examples of hard tissues. The biomechanical properties of each tissue vary owing to

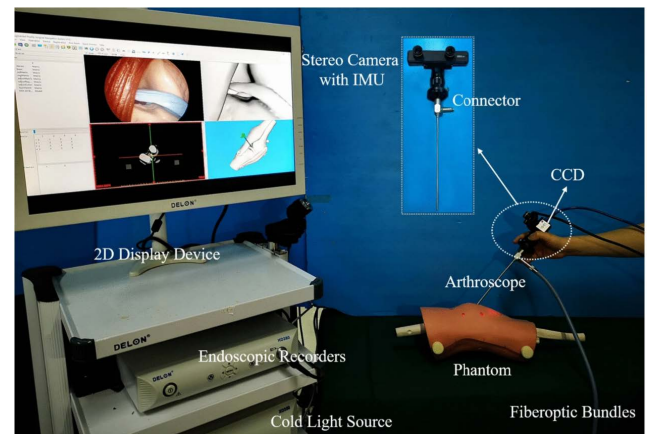


FIGURE 3. Setup for self-position tracking in knee arthroscopy as shown by Ma *et al.* [40].

differences in chemical composition and material orientation. Hence, in this section, we discuss the different biomechanical properties of tissues, the methods used to characterize these properties, and the constitutive models for soft and hard tissues. We only consider the tissues relevant for knee arthroscopy. From the review, 13 papers were selected based on material modeling. However, we relied on studies published outside our review period to provide a better understanding of a wide range of constitutive models.

1) BIOMECHANICAL PROPERTIES OF TISSUE

Skeletal soft tissues such as the articular cartilage, meniscus, ligaments, tendons, and muscles have solid and a fluid phases. Collagen and/or elastin fibers as well as proteoglycans constitute the solid phase. It contributes around 10 to 30% of the total wet weight of skeletal soft tissue with the remaining being fluid phase [69]. In contrast, hard tissues, such as bone, have a relatively low water content and are primarily composed of minerals. The properties exhibited by soft tissues include nonlinearity, anisotropy, viscoelasticity, and quasi-incompressibility [70]. In contrast, hard tissues are distinguished by their strength, strain rate effects, fracture, and fatigue properties [71].

In soft tissues, the relationship between stress and strain is nonlinear under the influence of an external force. Viscoelasticity is a time-dependent behavior in which a material exhibits both viscous and elastic properties during deformation. These include stress relaxation, creep, and hysteresis effects. Stress relaxation is the change in stress as a function of time when the strain of the soft tissue remains constant. Creep is a gradual change in soft tissue strain caused by a constant external force. The stress-strain curve of soft tissue during unloading clearly lags behind that of loading, which is known as hysteresis. The mechanical characteristics of soft tissues are influenced by the direction of the fiber components. The distinct material properties in different material directions are referred to as anisotropy. Soft tissues are mostly

TABLE 2. Constitutive models for the tissues involved in orthopedic surgery simulator.

Tissue Type	Material Model	Reference
Cartilage	Linear elastic, isotropic and homogeneous	[46], [47]
	Fibril reinforced biphasic (viscoelastic fibril, poro-hyperelastic matrix)	[48]
	Strain-dependent poro-viscoelastic	[49]
Meniscus	Linear elastic, isotropic and homogeneous	[46]
	Transversely isotropic, biphasic	[50]
	Linear elastic, transversely isotropic	[47]
	Linear viscoelastic	[51]
	Poroviscoelastic	[52]
Ligaments	Linear elastic, isotropic and homogeneous	[53]
	Transversely isotropic, hyperelastic	[46], [54]
	1-D non-linear spring	[47]
Tendons	Anisotropic elasto-damage	[55]
	Non-linear, rate dependent, and anisotropic	[56]
	Fiber reinforced, incompressible,	[57]
	Anisotropic, viscoelastic	[58]
Muscles	Hyperelastic, transversely isotropic	[59]
	Viscoelastic, anisotropic damage	[60]
Blood vessels	Pseudoelastic	[61]
	Poroelastic	[62]
	Viscoelastic	[63]
Cortical bone	Linear elastic, isotropic and homogeneous	[64]
	Isotropic, plastic damage	[65]
	Linear elastic, nonlinear viscoelastic	[66]
	Orthotropic, fracture	[67]
Medullar bone	Linear elastic, isotropic and homogeneous	[64]
	Orthotropic, damage	[68]

composed of water, which adds to their quasi-incompressible features.

The stress-strain curve is commonly used to study the mechanical behavior of tissues. Tensile testing of soft tissue results in a stress-strain curve with a toe region, an elastic region, a plastic region, and a fracture region. This behavior is caused by the straightening of collagen fibrils with increased loading and subsequent fracture. Within the elastic limit, if the load is removed, tissues can regain their original shape. However, in the plastic region, irreversible changes occur owing to the development of microfractures in the fibrils and, eventually, the tissue breaks [69]. When hard tissue is loaded, it responds elastically until it reaches the yield point. Plasticity and damage occur after passing this yield point. Plasticity refers to permanent deformation upon unloading, similar to soft tissue deformation, whereas damage is related with to formation of microcracks. Fracture, unlike damage, is caused by the formation and propagation of macroscopic cracks [72], while property fatigue is associated with failure due to cyclic loading. Characterization of the biomechanical properties require a variety of methods. This is discussed in the following paragraphs.

2) METHODS FOR CHARACTERIZATION OF BIOMECHANICAL PROPERTIES

The characterization of the highly complex behavior of biological tissues is a demanding task. The material properties vary at various hierarchical levels, as well as in different directions [50]. In addition, age, sex, and health condition are also influencing factors. Mechanical testing, ultrasonic testing, and computational methodologies are

commonly employed to obtain data to fit the constitutive equations. Owing to the constraints of in vivo studies, mechanical testing is considered the gold standard for characterizing biomechanical properties. Tension, compression, bending and torsion are conventional mechanical characterization techniques [69]. These experimental techniques facilitate the creation of a wide range of constitutive models, from basic to complex. The selection criterion for the test is to create a set-up that is as close to an in vivo condition as possible. Accordingly, the sample size, shape, boundary condition, and loading condition for the experiment vary.

Computational approaches have recently drawn increasing attention owing to the destructive and time-consuming nature of mechanical testing. These methods are promising when it comes to patient-specific modeling [39]. Furthermore, these models not only lead to the replication of complex structural and material behaviors of tissues but also have a high predictive power.

Usually, material attributes are formulated as an input for simulating a biomechanical system. Grytz *et al.* [73] effectively incorporated heterogeneous and anisotropic material properties into eye-specific finite-element models using a mesh-free approach. Obrezkov *et al.* [58] used an absolute nodal coordinate formulation to analyze the deformation of an Achilles tendon with anisotropic elastic features. However, material properties can also be extracted from a simulated model using reverse engineering techniques. Bojairami *et al.* [74] extracted nonhomogeneous tissue properties in real time using cohesive elements. Kim and Lee [75] identified material features using the virtual fields method based on the finite element scheme (FE-VFM), in which

the full-field displacements were experimentally measured and then mapped onto finite element meshes. Seyfi *et al.* [52] optimized constitutive parameters of the human meniscus using an inverse finite element method.

Another approach for material characterization is the use of machine learning (ML) techniques to train a model and then use this model to accurately predict the effective mechanical properties of patient-specific models, mainly in real time. Many researchers have used this concept with the help of different machine learning tools to develop mechanical models in divergent contexts. For instance, Hashemi *et al.* [76] homogenized liver tissue from many samples of heterogeneous models and trained this database using artificial neural networks (ANNs). Santhanam *et al.* [77] proposed a similar machine learning approach, but used a constrained generalized adversarial neural network (cGAN) to train the models for predicting the tissue elasticity of the lungs. Pellicer-Valero *et al.* [78] adopted this strategy to develop a real-time biomechanical model of the liver that considers various loading and material characteristics. Mendizabal *et al.* [79] applied U-Mesh, a data-driven approach that relies on the U-Net architecture, to simulate hyperelastic behavior in real time in liver tissue. Lauzeral *et al.* [14] employed a model order reduction technique to compute the material response during breathing simulations.

3) CONSTITUTIVE MODELING OF TISSUES

A constitutive material model is a mathematical model based on fundamental physical principles that aims to recreate what has been observed in reality. In other words, it encapsulates the material behavior through the stress-strain relationship. Many computational models are available based on these relationships.

Linear elastic models are used to define tissues with a generalized Hookean relationship, in which the stress is proportional to the strain within the elastic limit of the material and the proportionality constant is known as the stiffness matrix. This stiffness matrix requires 21 elastic constants to characterize the anisotropic nature of the tissues. It is possible to approximate the anisotropic condition to orthotropic, transversely isotropic, or isotropic after considering the structural alignment of the fibers. In orthotropic materials, the properties vary in three mutually perpendicular directions, and require nine elastic constants in the stiffness matrix. In transversely isotropic materials, the properties are the same along a plane, but different in the perpendicular direction. Here, the number of elastic constants is reduced from nine to five. Isotropic material properties are the simplest assumptions in linear elastic models, with two elastic constants: Young's modulus and Poisson's ratio.

Linear elastic material models are utilized to ensure calculation simplicity and to reduce computing expenses. Although this model is acceptable for small strain analysis, the linear model is not sufficient for realistic simulation of

soft tissues because of the significant nonlinear deformation experienced by living tissues.

Hyperelastic models are used to characterize the nonlinear stress-strain behavior. Several hyperelastic models have been developed using the strain-energy potential function, including the Mooney-Rivlin, Neo-Hookean, Arruda-Boyce, and Ogden models. Viscoelastic models are employed to simulate time-dependent behavior during creep and stress relaxation. The Maxwell, Voigt, and Kelvin models are the conventional viscoelastic models. The Maxwell model depicts a dashpot and a linear spring in series, whereas the Voigt model depicts parallel connection between the two. The Kelvin model is a combination of a Maxwell element and linear spring. The behaviors of loading and unloading are modeled separately in pseudoelastic modeling. Knowing that soft tissues are fluid-saturated, incorporating fluid parameters into the model and presenting these models as biphasic models would strengthen the prediction performance. Poroelastic formulations consider the flow of an interstitial fluid through a porous medium. The biphasic, poroelastic model allows for the addition of permeability, which is the most significant fluid property, and the creation of a more sophisticated model. In another approach, the fibril-reinforced model, the solid phase is considered fibrillar and non-fibrillar.

Combining the above models and/or improving the mathematical formulation behind each model that suits the problem at hand can aid in capturing accurate material properties. Nonlinear hyper-viscoelastic models [80], nonlinear time-dependent model includes salient microstructural deformation mechanisms [81], and anisotropic viscoelastic [82] are few of the constitutive models developed for soft tissues during the review period.

The aforementioned models would be insufficient for modeling plastic, damage, and/or fracture behavior in hard tissues. Precise information on damage and fracture behavior could aid in the development of better orthopedic implants [65]. The details of these models are out of scope of our paper. However, from the broad spectrum of available constitutive models, we identified a few and listed them in Table 2.

D. SOFT TISSUE DEFORMATION AND CUTTING SIMULATION STRATEGIES

Soft tissue modeling is the core of surgical simulation. In interactive surgical simulation, meeting the needs of real-time simulation without sacrificing physical realism is challenging. Many improvements to traditional modeling methodologies have been proposed to address this difficulty. All identified simulation strategies for soft tissue modeling were categorized into three groups in this paper: mesh-based, meshfree-based, and hybrid modeling methods [25]. Mesh-based modeling methods mainly include the traditional finite element method and its variations, which are used to improve the computational efficiency and modeling accuracy. Simpler techniques without meshing the problem domain fall into the meshfree-based group. The term hybrid method refers to an approach that combines two or more

modeling techniques. Our review covers not only the tool-tissue interaction associated with deformation but also the simulation of the cutting technique. Under the category of simulation strategies, 34 recent studies were selected using the PRISMA protocol. 18 of these articles dealt with mesh-based modeling approaches, ten with meshfree modeling techniques, and six with hybrid modeling techniques. Overall, 28 papers were mainly concerned with soft tissue deformation, while the others also addressed soft tissue cutting.

1) MESH-BASED MODELING METHODS

Finite-element-based approaches are widely accepted mesh-based modeling method in the field of soft tissue deformation. The finite-element method is based on the continuum mechanics technique, which involves discretizing the continuum into finite volume elements and connecting them at nodes. The mechanical behavior of the soft tissues is then described using an appropriate constitutive law. Finally, nodal parameters, such as displacement, are determined by solving the governing equation with specified loading and boundary conditions. The realistic material modeling capacity makes FEM popular in the spectrum of computational biomechanics, despite the fact that it requires significant computing power.

Traditional FEM has been effectively used for a wide range of biomechanical models of both soft and hard tissues. However, the inefficiency of this approach in achieving a minimum visual refresh rate of 30 Hz and a minimum haptic refresh rate of 1000 Hz limits its application in surgical simulations. As a result, several alterations and modifications have been made to the traditional FEM in order to reduce computational complexity and achieve a closer accuracy to the biomechanical system.

The formulation employed (total or updated Lagrangian), integration scheme (implicit or explicit) and element type are the aspects on which the efficiency of FEM is based. Total Lagrangian Explicit Dynamics (TLED) is a numerical scheme used for accelerating the FEM. The implementation of this algorithm is particularly suited for soft tissue analysis due to its capability of incorporating nonlinear and anisotropic material behavior [87]. However, TLED is not ideal for real-time implementation because of the explicit time integration strategy. The requirement for a small time-step constraint in an explicit scheme may lead to overshooting problems.

The simulation and real-time visualization of thermal energy distribution is an important feature of electrosurgery. Polousky *et al.* [96] reported electrosurgery as an effective tool for arthroscopic meniscectomy. Zhang and Chauhan [90] proposed a thermal analysis under tool-tissue deformation based on the fast explicit dynamics finite-element algorithm (FED-FEM). The FED-FEM uses an explicit time integration scheme and computes the nodal load, in this case thermal load, at the element level. There is no need to invert the system stiffness matrix at each level, assemble the global

stiffness matrix, or use the iterative Newton-Raphson at any stage in the algorithm. Furthermore, the precomputation of constant parameters makes it ideal for real-time or near-real-time applications. In their later work, they combined thermo-visco-hyperelastic finite element techniques based on finite-strain thermoelasticity with TLED [91].

Soft tissue is treated as linearly elastic in the majority of existing surgery simulators. This allows the stiffness matrix to be computed ahead of time, reducing the time spent online. Obviously, this assumption fails to include the geometric and material nonlinearities of soft tissues. Therefore, an appropriate formalism for accounting for these linearities must be devised in surgery simulations. The corotational FEM can be used to address geometric non-linearity in soft tissues, such as large deformations. Marinković and Zehn [86] proposed corotational finite-element formulation for virtual reality-based surgery simulators. This method solves the problem of artificial enlargement of the model caused by moderately large rotations, while maintaining the benefits of traditional linear FEM. Bui *et al.* [94], [95] also used a linear elastic material based on a corotational formulation for real-time simulation of needle insertion into soft tissue. The assumption of small strain theory and linear material response, which are clearly not satisfied in many clinically relevant cases, is the fundamental disadvantage of the corotational formulation.

To account for material nonlinearity, Tabatabaei *et al.* [97] demonstrated the concept of the stress-strain relationship of soft tissues in a non-integer order. This research is still in its early phases. However, this would provide a new direction for the advancement of soft tissue analysis. In addition to modeling dynamic behavior, their model can be rearranged into a state-space form. Under the premise of state-space modeling, it is worthwhile to mention the Kalman filter-finite element method (KF-FEM). The Kalman filter is a well-known algorithm for state estimation in the form of feedback control. Xie *et al.* [83] proposed the KF-FEM method for real-time and accurate modeling of soft tissue deformation. This method allows online estimation of soft-tissue deformation from the local measurement of displacement by formulating the deformation of the soft tissue as a filtering identification process. To analyze the nonlinear soft tissue behavior, an extended (nonlinear) Kalman filter is combined with the traditional nonlinear FEM [84]. The computational head can be further reduced by lowering the number of states of model without compromising its physics [85].

Model-order reduction (MOR) is another promising topic. MOR methods enable real-time simulations by reducing the dimension of a multidimensional physical model. The proper orthogonal decomposition (POD) method is frequently applied in soft tissue mechanics [85], [89]. Gao and Shang [89] achieved real-time simulation in vascular interventional surgery using POD to decompose position and then singular value decomposition (SVD) to minimize the cost function. Calka *et al.* [88] developed a MOR method based on machine learning (ML) techniques and applied it to

a FE model of the human tongue to predict quantitative movement after orofacial surgery. They chose SVD as MOR technique and a recurrent neural network as the ML tool.

In the context of surgical simulation, the use of ML has been investigated in many ways. One method is to utilize the constitutive relationships of accurate FE models to predict the material properties. This is already discussed in Section IV-C. Another option is to use ML models to forecast the nodal parameters and/or their derivatives. Wu *et al.* [98] investigated how real data obtained during a robotic endoscopic surgical procedure could be used to compensate for incorrect FEM modeling results. Using the mesh vertex location of a finite element model as the input, they trained a network to predict the correction factor that adjusts for the gap between the simulation and observation. The ML approach can also be used to improve computational efficiency. Meister *et al.* [87] employed a deep-learning method to accelerate the time integration of a TLED. Although these training processes are time consuming, once trained, these models assist in achieving faster real-time responses.

Mesh refinement is an effective method for increasing the simulation accuracy. However, mesh refinement of the entire organ or tissue under consideration reduces the simulation rate. This problem can be solved using an adaptive mesh refinement. The desired simulation accuracy and rate can be obtained simultaneously using a refined mesh at the surgical site and a coarse mesh at the nonsurgical site [92].

HoloFEM is an innovative software application developed by Logg *et al.* [99] that allows for the automatic generation of finite element meshes and simulations by scanning the surroundings using Microsoft HoloLens. Despite the fact that they only conceptually simulated temperature and air quality, this research is intriguing in the context of the growing usage of augmented reality, virtual reality, and mixed reality technologies in patient-specific surgery simulators [100].

In the boundary element method (BEM), mechanical behavior is modeled by using surface integral equations. This approach is simpler because it minimizes the degrees of freedom (DOF) while computing deformation. Wang *et al.* [101] used this technique for real-time simulation of soft tissues with a tumor. The mesh-based techniques are summarized in Table 3.

2) MESHFREE-BASED MODELING METHODS

In the meshfree modeling approach, the continuum is modeled using discrete points. Mass-spring system modeling (MSM) is a widely used meshfree-based modeling method because of its simplicity and less time-consuming calculations. However, accurate modeling of material properties is a difficult problem in MSM. Moreover, an increase in the number of springs increase the system stiffness. Both these issues are key aspects to consider when dealing with soft tissue deformation. Many improvements have been proposed for classical mass-spring models to address these shortcomings. Li *et al.* [106] presented new flexion springs in a mass-spring model for real-time shape restoration.

This improved model is based on a surface representation without internal geometry, making it unsuitable for difficult surgical operations like tearing and cutting. Tan *et al.* [102] introduced the concept of a virtual stress layer to improve realism. However, this method has an increased computational cost and necessitates the use of parallel computing. As part of modeling stump soft tissue deformation in stump-socket interactions, Ballit *et al.* [110] developed a mass-spring system with a correcting spring and applied on a hexahedral mesh. They integrated additional springs named “corrective springs” into the mass-spring system to incorporate the incompressible behavior of soft tissues.

Another method, called ChainMail, is also recognized in real-time soft tissue simulations. The problem domain in ChainMail is modeled as a chain of linked elements, with motion between neighboring parts limited in the same manner as in a chain. To address complex mechanical behaviors, Zhang *et al.* [111] developed the time-saving volume-energy conserved ChainMail (TSVE-ChainMail), an enhanced ChainMail based on volume and strain energy conservation. However, their method benefits isotropic materials solely in terms of computing efficiency.

Large deformations in complex geometries can be addressed using a meshless method. This has the benefit of not requiring a predefined mesh, such as in FEM. Meshless methods based on the element-free Galerkin (EFG) method [107] and radial basis function point interpolation method (RPIM) [112] are used for accurate computation of soft tissue deformation for surgical simulation. The meshless total Lagrangian explicit dynamics (MTLED) approach employed by Joldes *et al.* [107] provides reliable result for large compressive strains around the tool-tissue contact zone. The EFG approach has several drawbacks, one of which is the difficulty in enforcing essential boundary conditions. This obstacle is addressed by the Kronecker delta function feature of the RPIM shape functions, which allows the essential boundary conditions to be implemented as easily as in the FEM.

During the last five years, the position-based dynamics (PBD) method has attracted the interest of researchers in the field of soft tissue simulation. The traditional methods start with forces, then utilize Newton’s second law to obtain acceleration, any integration scheme to calculate velocity, and finally extract the position from the velocity. In contrast, PBD [113] works directly on the position to solve geometrical constraints. PBD has the advantages of being easier to implement, having more control over explicit integration, and being free of instability issues. However, it ignores the accurate modeling of the physical properties of soft tissues. This geometries-based approach has recently been employed to mimic brain deformation during catheter insertion [103] and to simulate periodical beating of the human heart [104].

Zhang *et al.* [108] modeled large nonlinear deformation in soft tissue based on reaction-diffusion mechanics via neural dynamics. They used cellular neural networks (CNN) constructed to modeling both the reaction-diffusion propagation

TABLE 3. Classification of mesh-based modeling methods for soft-tissue simulation.

Ref	Modeling methods	Tissue type / behaviors	Geometry discretization	Dis-	Computation efficiency / accuracy	Hardware Configurations
[83]	Kalman Filter combined with linear FEM	Human liver / Linear elasticity	1083 nodes and 4941 tetrahedral elements		0.01937, 52Hz visual refresh rate, 1000Hz force refresh rate	Intel® Core i7-8750 CPU @ 2.20 GHz, RAM 16 GB, 64-bit Windows 10
[84]	Extended Kalman Filter combined with non-linear FEM	Liver / Non-linear elasticity	1083 nodes and 4941 tetrahedral elements		50Hz visual refresh rate, 1000Hz force refresh rate	Intel® Core i7-8750, 2.20GHz CPU, 16GB RAM , GTX 1070 graphics card
[85]	Reduced order Extended Kalman Filter combined with non-linear FEM	Liver / Hyper elasticity	1083 nodes and 4941 tetrahedral elements		80Hz visual refresh rate, 1000Hz force refresh rate	Intel® Core i7-8750, 2.20GHz CPU, 16GB RAM , GTX 1070 graphics card
[86]	Corotational FEM	Liver / Linear elasticity	5192 faces, 640 nodes, 2598 vertices		34 FPS	Intel i3-2120 (3.3 GHz), NVidia 750 GTI
[78]	ML models trained on FEM, feedforward neural networks as ML tool	Liver / Hyper elasticity, first order Ogden model	11736 ± 3599 nodes		2ms to 5ms (model deformation), above 500Hz haptic feedback	Two-core i5processor, low end GT 840M GPU
[87]	Neural networks to accelerate the time integration of Total Lagrangian Explicit Dynamics (TLED)	Liver lobe / Anisotropic, Holzapfel – Ogden model	507 vertices and 1493 tetrahedral elements		Accurate displacement at time steps up to 20 times larger than TLED’s explicit time step	-
[88]	Machine-Learning based Model Order Reduction (MOR) method	Tongue / Mooney-Rivlin material model	7763 nodes and 8780 hexahedral elements		Sub-millimetric spatial accuracy	-
[89]	Finite Element Method and Model Order Reduction	Blood vessel / -	-		Around 150Hz FPS	16GB RAM, Intel Xeon (R) E51607 CPU, NVIDIA GeForce GT 730 GPU
[90]	Fast Explicit Dynamics Finite Element algorithm (FED-FEM)	Vascularised human liver / Neo-Hookean hyper elastic model	7872 nodes, 40021 linear tetrahedrons elements		t = 14.110 ms per time step	Intel(R) Core(TM) i7-8750H CPU @ 2.20GHz and 16.0GB RAM Laptop using a serial execution
[91]	Finite-strain thermoelasticity and total Lagrangian explicit dynamics	Human liver / Transversely isotropic neo-Hookean visco-hyperelastic model	3268 nodes, 18007 linear tetrahedrons elements		0.0002s per time step	GPU
[92]	Softness-based adaptive mesh refinement algorithm	Stomach lining / -	715 mass points, 1319 triangular patches, 3957 edges		28.7 FPS	Intel(R) Core(TM) i7-5500U CPU at 2.40 GHz, 8 GB ofRAM, and an ATI Radeon R9 M375 graphics card with 2 GB memory
[93]	Interactive cutting by allowing small gaps between the model boundary and the volumetric finite elements	Porcine liver / -	Hexahedron, triangular meshes for cut surface		The total computation time is much smaller than the sampling time for the visual rendering	CPU i7-4770K
[94]	Posteriori error-driven adaptive finite element approach	Liver / Linear elasticity	1179 DOF for the initial mesh		22 FPS	4 GHz processor
[95]	Corotational cut finite element method	Liver / Linear elasticity	-		Approximately 2.3 times faster than traditional FEM	-

FPS - Frames per second.

of mechanical potential energy and the non-rigid mechanics of motion to achieve real-time simulation, as shown in Fig. 4. This work was further extended to achieve stable model dynamics for soft tissue deformation owing to the nonlinear properties of the cellular neural network [109]. A summary of meshfree-based modeling methods is shown in Table 4.

3) HYBRID MODELING METHODS

Hybrid methods combine two or more modeling approaches by incorporating the benefits of each of these. Tang *et al.* [70]

proposed an improved soft tissue model by combining FEM with MSM and estimated the mass-spring model parameters using the finite element method. They showed that their model could trace material behavior very close to the physical system. Han and Lee [118] used Saint Venant–Kirchhoff model for modeling non-linear material behaviour and iteratively updated the local position using the PBD framework. However, they were unable to achieve a real-time simulation rate for the finer models. Luo *et al.* [116] and Xu *et al.* [115] integrated viscoelastic mass spring dampers

TABLE 4. Classification of meshfree-based modeling methods for soft-tissue simulation.

Ref	Modeling methods	Tissue type / behaviors	Geometry discretization	Dis-	Computation efficiency / accuracy	Hardware Configurations
[102]	Virtual stress layer modeling (improved MSM)	Lung / Viscoelasticity	Different models with masses 1100, 2600 and 4600		17, 58 and 71 FPS for quadra core, 25, 69 and 66 FPS for eight core	Different CPU cores
[103]	Position Based Dynamics (PBD)	Ovine brain / -	-		Close match with real brain deformations	Intel Core i7 6800k processor, 32 GB RAM, Titan XpGPU by NVIDIA Corporation with CUDA 10.1
[104]	Position Based Dynamics (PBD)	Heart / -	-		Greater than 30 FPS	Intel i7-6920HQ CPU @3.5 GHz,NVIDIA GTX 10808G RAM
[105]	Meshless physical model	Liver / Non-linear visco-elasticity	541 triangular patches		consistent haptic interaction with the presentation of visual effect	CUDA, GPU
[106]	Surface Mass Spring Model with flexion spring	Heart / Linear elasticity	1529 points and 3054 triangles		151.35 average FPS	Intel(R) Core (TM) i7-6700 CPU at 3.40 GHz, Intel(R) HD Graphics GPU, 8.00 GB RAM, and WIN10 64-bit OS
[107]	Meshless Total Lagrangian Explicit Dynamics (MTLED) algorithms incorporating a Modified Moving Least Squares (MMLS) method	Brain / Neo-Hookean material model	8769 nodes and 158,678 integration points		reliable results for compressive strains exceeding 70%	-
[108]	Reaction-diffusion mechanics via neural dynamics	Kidney / Non-linearity	1378 mass points		Force update rate 1000 Hz with around 600 mesh points, visual feedback rate 30Hz with around 3000 mass points	Intel® Core™ i7-5500U CPU at 2.40 GHz and 4 GB memory PC
[109]	Cellular Neural Network (CNN) method	Kidney / Non-linearity	1,378 nodes and 4,691 tetrahedrons		Force update rate 1000 Hz with around 1200 mesh points, visual feedback rate 30Hz with around 6500 mass points	Intel(R) Core(TM) i7-4770 CPU @ 3.40 GHz and 8 GB RAM PC

FPS - Frames per second.



FIGURE 4. Zhang et al. [108] used cellular neural networks to model soft tissue behavior of a kidney, and interfaced the simulation with a Geomagic Touch haptic device.

into position-based dynamics to simulate soft tissue deformation in real-time. To solve the defects of traditional mass springs, Ye et al. [114] combined them with a filling model, which could move and rotate freely. They claimed that including an infinite number of filling models with mass, inertia,

and volume properties would provide a more accurate simulation of the human tissue deformation behavior. Overall, hybrid approaches improve traditional methods by drastically reducing the computation time and complexity of soft-tissue deformation behavior. A summary of these hybrid modeling methods is presented in Table 5.

4) CUTTING

Other common interactions that must be considered for the development of a surgical simulator include cutting, drilling, and suturing. Robust cutting simulation requires a substantial amount of processing power in addition to the requirements of deformation modeling owing to topological and geometrical changes.

Byeon and Lee [93] handled interactive soft tissue cutting in real-time by approximating small gaps between the model boundary and volumetric finite elements. This method overcomes the computational burden of the addition degrees of freedom and prohibits the formation of ill-shaped elements. Bui et al. [94] demonstrated a real-time simulation of needle insertion into soft tissues using an a posteriori error-driven adaptive finite element approach. Indeed, the proposed local remeshing, which is based on the error between the accurate analytical solution and the FEM, is sufficient to perform

TABLE 5. Classification of hybrid modeling methods for soft-tissue simulation.

Ref	Modeling methods	Tissue type / behaviors	Geometry discretization	Dis-	Computation efficiency / accuracy	Hardware Configurations
[114]	Filling model and Mass Spring Model	Liver / -	-		Computation time - 1.58 ms, 63 FPS	GPU
[115]	Position Based Dynamic method integrated with viscoelastic Mass Spring Damper method	Liver and gallbladder / Viscoelasticity and nonlinearity	650 nodes, 1938 springs		Greater than 30 FPS	Intel Core i7-7700 CPU@3.6 GHz and NVIDIA GTX 1070 GPU
[116]	Mass Spring Modeling and Position Based Dynamics	Liver / Viscoelasticity and nonlinearity	2024 masses		7.75 s, refresh rate 1140 Hz	Inter(R)Xeon(R) CPU E5-1650v3 and the graphics card is the NVIDIA Quadro M4000
[117]	Tetrahedron mesh and Position Based Dynamics with cluster-based shape matching	Liver / -	85240 vertices, 170277 triangles, 885163 tetrahedrons, 170854 physical particles, 3892 clusters		Soft Deformation 36.8ms, haptic Rendering 1.05ms, topology update 98.3ms, mesh skinning and graphics rendering 20.83ms	NVIDIA GeForce RTX 2080Ti, an Intel i9-9900K CPU, 16GB RAM, and two haptic devices
[118]	The Saint Venant–Kirchhoff model, Position Based Dynamics (PBD)	Liver / Non-linearity	596 tetrahedral elements		Computation time 10 ms	Intel Core(TM) i7-7700 CPU @ 3.60 GHz and 64GB memory
[119]	Position Based Dynamics and meshless method	Liver, Spleen and Gallbladder / Linear elasticity	Number of spheres 570, 452 and 466		Time for deformation 6.25, 2.65 and 2.14 ms, time for cutting 9.52, 3.33 and 2.58 ms, haptic rate around 1kHz	NVIDIA GeForceGT 630, Intel(R) Core(TM) i7-4790 CPU (3.60 GHz, 8 cores), and 8G RAM

FPS - Frames per second.

real-time simulations. However, they did not take into account modeling errors, such as those caused by tool-tissue interactions and material modeling choices. Bui *et al.* [95] applied the corotational cut FEM to needle insertion simulations and used a background mesh that did not necessarily conform to the boundary of the simulated object. The extended finite element method (XFEM) addresses crack propagation and material interface problems. Gutiérrez and Ramos [120] used XFEM framework for soft tissue cutting.

Shi *et al.* [105] proposed a meshless physical model based on point elements to improve visual and haptic rendering. A hybrid modeling method combining geometric metaballs and the meshless method [119] was used to simulate real-time dissection in a VR-based laparoscopic surgery simulator.

E. HAPTIC FEEDBACK

Kinesthetic haptic feedback enables physical interaction with a digital twin, and is identified as a critical functionality in all three user scenarios described in Section II. We use the terms haptic feedback and kinesthetic feedback interchangeably. From our literature review, 16 articles on haptic feedback were included. Nine articles described haptic device or actuator development, six articles described simulator development, and one article presented a method for predicting haptic feedback from expert surgeon behavior. An overview is presented in Table 6.

A fundamental principle in haptic feedback is the trade-off between stability and transparency. The more accurate a system is displayed, the more stability is compromised. This is because the kinesthetic system is based on imperfect

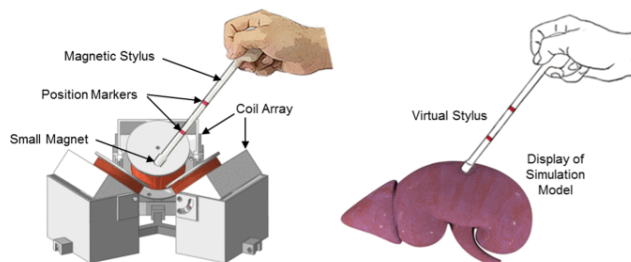


FIGURE 5. 3DOF haptic system for palpation based on magnetic levitation, as shown by Tong et al. [121].

electro-mechanical design. The more accurate the system is rendered, for example a virtual spring with high stiffness, the more prone the system is to time delays, nonlinearities, actuator saturation, and sensor and actuator accuracy [122]. Therefore, efforts in the design of haptic systems are aimed at balancing this trade-off. The system is said to enter a limit cycle if it exhibits a self-sustained oscillation, even if the system is perturbed or the oscillations are bounded [123], [124].

Impedance and admittance control are the two primary approaches for controlling closed-loop active kinesthetic feedback systems. Impedance control is when a user applies a motion to the system, position sensors detect displacement, a force is computed as a function of position, and a force is rendered to the user through the haptic device. Admittance control is when the user applies a force to the system, a force is detected by force sensors on the haptic

device, a motion (displacement or velocity) is computed as a function of force, and the user feels a motion [123]. While impedance control enables easy rendering of no impedance (infinite admittance), for example, a surgical tool moving in free space, it suffers from instability when subjected to high impedance. Conversely, admittance control allows for rendering of high impedance but suffers from a lack of transparency at low impedance. This is because admittance devices must actively mask inertia and friction owing to the reflected inertia and friction from high-g geared actuators [125]. Admittance devices are also usually more expensive owing to costly force sensors and higher requirements for tolerances and stiffness. Consequently, most commercial haptic systems employ impedance control. However, the range of achievable dynamics, or z-width, is higher for admittance control than impedance control [125], [126]. Recently, Ha-Van *et al.* [127] demonstrated the use of admittance control in a drill mockup for arthroscopic surgical training.

A widely adopted rule of thumb is that haptic systems require a refresh rate of at least 1 kHz for stability and smooth perception of stiff materials, and a few hundred Hertz for soft materials [124]. Human cutaneous mechanoreceptors, such as the Ruffini and Pacinian corpuscles, can sense frequencies up to 500 Hz [128]. Therefore, the sensation of touch is much more sensitive than the visual sensation. Colgate *et al.* [129] showed that for an impedance-controlled virtual wall, the sampling time influences stability. Other factors that affect stability include physical and virtual damping. Moreover, they defined a passivity condition as:

$$b > \frac{KT}{2} + |B| \quad (1)$$

where b is the physical damping (or friction) of the haptic device, K is the virtual wall stiffness, B is the virtual wall damping coefficient, and T is sampling time. Interaction with stiff virtual objects requires higher physical damping than that with soft virtual objects. To overcome this instability issue, virtual coupling was proposed in the same study by introducing a virtual spring and damper between the haptic interaction point and virtual object. The spring and damping parameters can then be tuned to guarantee stability. Furthermore, the god-object method was introduced by Zilles and Salisbury [130] to visually prevent penetration of the virtual object, and thus enhancing the perception of stiffness.

For multi-DOF haptic device kinematic configurations, dynamic transparency, size of the work space, actuation power, and stiffness are all important physical properties to be considered. Various kinematic structures found in existing commercial haptic devices perform differently with respect to these requirements. The five-bar linkage configuration, as found in the Phantom Premium, stands out as the most dynamically transparent, whereas the delta configuration, as found in Force Dimension devices, is stiffer. The serial linkage configuration, as found in cheaper devices such as Geomagic Touch, is significantly softer.

The requirements for actuation of active impedance-type haptic devices are low inertia, low friction, low torque ripple, back-drivability and low backlash, [124]. As such, the most commonly implemented actuators in haptic devices are permanent magnet direct current (DC) motors, coreless DC motors, and brushless DC motors because torque can be controlled with current [123]. However, other actuation methods have also recently been explored. Wu *et al.* [131] explored control strategies for the control of a pneumatic artificial muscle (PAM)-based haptic device, and found that an adaptive fuzzy sliding mode control force loop-based system provided best force feel. Tong *et al.* [121] designed a 3DOF haptic system for palpation based on magnetic levitation, using a magnetic stylus and stereoscopic tracking for position sensing, as shown in Fig. 5. By controlling the current-carrying coils using a self-adaptive fuzzy proportional–integral–derivative (PID) algorithm, different virtual tissue stiffnesses can be rendered. They conducted a user study with 22 participants for liver tissue assessment, and found that their device performed as well as a Phantom Omni/Geomagic Touch commercial haptic device with respect to the quality of experience.

Closely related to actuation is the transmission of forces from actuator to the haptic device, where traditional methods for impedance devices are capstan and direct drives [123]. Recently, Lebel *et al.* [132] compared the use of magnetorheological (MR) clutches to lower reflected inertia of haptic devices. They found the MR clutch system to have approximately 50 % more bandwidth, 190 % less reflected inertia, and 66 % more damping than a DC-motor system. Moreover, as shown in Equation 1 is removing energy through damping an effective way of stabilizing the haptic system. Recently, there has been a trend towards the removal of energy from a system in a controlled manner, referred to as semi-active haptic rendering. Nakamura and Motoi [133] recently used a powder brake in combination with a constant-torque spring for the haptic control of an exoskeleton haptic device. Hooshiar *et al.* [134] used position-controlled permanent magnets to control the friction between a magnetorehological elastomer (MRE) and a ferromagnetic shaft for haptic feedback in robot-assisted cardiovascular interventions. Pepley *et al.* [135] used material fracture to mimic the insertion of a needle, and Yeh *et al.* [136] used piezoelectric actuators to control friction for haptic feedback. Huang *et al.* [137] designed a haptic system based on an MR-damper piston. Additionally, Choi *et al.* [138] introduced a high force density soft layer jamming brake (SLJB) concept for soft robotics.

Several recent studies have focused on the haptic rendering of drilling procedures. Maier *et al.* [139] used a finite-state machine approach on a Haption Virtuose 6D commercial device to simulate K-wire drilling for hand surgery. Kaluschke *et al.* [140] demonstrated a novel algorithm for material removal based on the god-object method and implemented their algorithm on a Kuka LBR robot for 6DOF high-force feedback (up to 200N). Fekri *et al.* [141] used a recursive neural network with LSTM architecture to capture

TABLE 6. Recent studies describing haptic feedback for surgical simulation.

Study	Contribution	Medical Application	Haptic Device	Actuation Principle
[134]	Device development	Cardiovascular surgery	Custom design	Magnetorheological elastomer
[141]	Use of deep learning to capture expert behavior and predict haptic feedback	Surgical drilling	Geomagic Touch with drill attached	DC-motor
[132]	Device development	-	Custom design	DC motor + magnetorheological fluid clutch
[143]	Simulator development	Femoral nailing	Entact W5D with custom drill	DC-motor
[145]	Simulator development	Hand palpation	Geomagic Touch	DC-motor
[140]	Drilling algorithm development	Hip replacement	Kuka LBR robot	DC-motor
[137]	Actuator design	-	Custom design	Magnetorheological fluid damper
[127]	Device development	Surgical drilling	Custom design	DC-motor
[133]	Device development	-	Custom design	Powder brake with constant torque spring
[136]	Device development	Palpation	Custom design	Piezoelectric actuator + friction
[131]	Device development	-	Custom design	Pneumatic artificial muscle (PAM)
[139]	Drilling simulation development	K-wire drilling for hand surgery	Haption Virtuose 6D with custom drill	DC-motor
[135]	Device development	Needle insertion	Custom design	Material fracture (passive)
[121]	Device development	Palpation	Custom design	Magnetic levitation
[144]	Method for haptic guidance	Hearth catheterization	Novint Falcon	DC-motor
[142]	Simulator development	Neurosurgical aneurism clipping	Geomagic touch with custom clipping forceps	DC-motor

expert behavior during surgical drilling. This behavior was intended for the haptic guidance of novice surgeons during training. They implemented their system on a Geomagic Touch haptic device with an attached drill. Moreover, using voxel-based 3D-geometry, the drilling resistance was controlled by exchanging stiffness at a rate of 10 Hz.

Some studies have modified commercial haptic devices for realism. Gmeiner et al. [142] used two Geomagic Touch haptic devices with custom clipping forceps for aneurysm clipping simulation. Racy et al. [143] developed a femoral nailing simulator using an Entact W5D haptic device with a custom 3D-printed drill handle. They also included intraoperative fluoroscopy in their simulation environment by using gVirtualX-ray library. Halabi and Halwani [144] presented a method for creating haptic guidance tunnels for pre-operative path planning and training. Their system was implemented on a Novint Falcon haptic device and was demonstrated for heart catheterization. Finally, nine studies described in Section IV-D reported the use of Geomagic Touch haptic devices in their applications.

F. SYSTEM ARCHITECTURES AND EXISTING FRAMEWORKS

For real-time interactive simulation, a major obstacle is to achieve a sufficient haptic refresh rate of 1 kHz based on potentially computationally expensive dynamic, deformable object, cutting, or material removal simulations, paired with a real-time visual feedback of 30 Hz. One way to deal with this is to separate haptic, deformable objects and visual simulations into separate threads. Peterlik et al. [146] introduced a constraint-based method called multirate compliant mechanisms, where the dynamics of virtual objects are computed at a low rate, and the interaction forces to the high-rate haptic

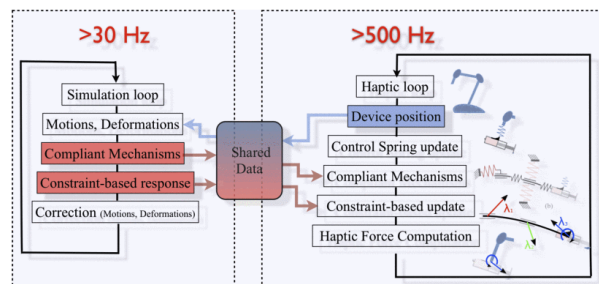


FIGURE 6. Multirate compliant mechanisms as described by Peterlik et al. [146].

thread are formulated as a constraint-based problem using Lagrange multipliers. This method handles complex interactions between medical devices and anatomical structures. The interaction equations are built at low rates and then shared with a separate high-rate haptic thread. An illustration is shown in Fig. 6.

Several interactive simulation frameworks have been used to develop surgical simulations. The multirate compliant mechanism method was developed using the simulation open framework architecture (SOFA) platform. This open-source C++ library was described by Faure et al. [147], and employs a multi-model representation consisting of deformation models based on MSM or corotational FEM, collision models based on sphere mapping, and visualization models where the mesh size can be different from the deformation models. This framework uses mapping functions between different models in a hierarchical system. SOFA also supports GPU (Graphics Processing Unit)-based computations. From the included studies, three reported the use of the SOFA

framework in their development [89], [94], [95]. Another popular C++ simulation framework reported in the literature is Chai3D. From our review, five studies reported the use of the Chai3D framework in the development of their simulators [127], [138]–[140], [144]. This framework also uses separate threads for simulations, haptics and visualizations. A third framework, OpenHaptics, has also been frequently reported in combination with Geomagic haptic devices [108], [109], [145], [148]. Other reported frameworks include Toia plugin with Unreal Engine [143], Bullet [142], and VEGA [121].

Recent developments in GPU computing have the potential to accelerate simulation speeds, but require system architectures compliant with parallel computations. The CUDA framework allows easy GPU implementation. Shao *et al.* [149] utilized a multi-GPU architecture with CUDA-framework to perform virtual reality interactions, including soft-object hybrid deformation based on the TLED- and fast lattice shape matching methods, cutting simulation based on TLED and virtual node algorithm, and cutting with bleeding effects based on Lagrangian particle dynamics. They compared performance in the three interaction scenarios using CPU, single GPU and multiple GPUs. They found that the multi-GPU approach accelerated performance by a maximum of 14.5 times compared to the CPU, achieving a frame rate of 25 FPS. Kaluschke *et al.* [140], Ye *et al.* [114], Segato *et al.* [103], Gao and Shang [89] and Zhang *et al.* [91] also reported using CUDA for GPU implementations.

V. TOWARDS A DIGITAL TWIN

In Section IV, we have reviewed the literature and presented state-of-the-art methods with respect to a digital twin for arthroscopic knee surgery. We have identified the key components and state-of-the-art techniques needed for the realization of such a system, such as patient-specific imaging, real-time intraoperative data collection techniques, material models for biomechanical tissue, tissue deformation simulation, cutting simulation, virtual interaction, haptic feedback, and system architectures. However, analyzing these findings in relation to the presented user scenarios shown in Fig. 1, we have identified gaps where the current state-of-the-art, to our knowledge, has not yet presented solutions needed for a true digital twin. Thus, we introduce a new section presenting a conceptual macro-level system of a digital twin for arthroscopic knee surgery, discussing applicability of the findings from Section IV in the identified subsystems. The macro-level design is shown in Fig. 7, and the following sub-sections describe the respective boxes as presented in the figure.

A. DIAGNOSIS DATA

After consultation with the physician, the patient receives a diagnosis. The *diagnosis data*, a qualitative description of the mechanism of injury, resulting in damage, and experienced pain, is saved to the *electronic patient record*.

B. ELECTRONIC PATIENT RECORD

Following our arthroscopic digital twin definition, *virtual information that fully describes a patient-specific biomechanical system*, we acknowledge that it is difficult to describe all parts of a joint with models. Other factors affecting the treatment, such as pain and health conditions, should be included. As such, we argue that a qualitative description of the *diagnosis data*, which is widely adopted in the healthcare system, should follow the digital twin.

C. PATIENT SPECIFIC IMAGING

Analyzing the findings from Section IV-A, we identify MRI as the most relevant modality for a true knee digital twin because of the ability to recreate internal anatomical structures of both soft tissues and bone structures. As shown by Sun *et al.* [33], a healthy knee MRI model can be automatically segmented into 12 different anatomical structures in minutes. The segmented structures were the cortical bone, medullary bone, PCL, ACL, muscle, artery, collateral ligaments, tendons, menisci, fat, and veins. An assembly model consisting of 12 individual STL files or voxel models form the *digital anatomy*. More work is needed to establish a robust automatic detection and segmentation of pathologies, such as a partially torn ligament.

D. MATERIAL DATABASE

As shown in Section IV-C and Table 2, extensive efforts have been made in terms of developing accurate material models of biomechanical tissue. Although some imaging modalities can estimate in vivo biomechanical properties as discussed in Section IV-A, we regard patient-specific collection of material properties as too costly and time consuming given the current state-of-the-art. Instead, we propose a database of predefined material constants for the respective tissues. The choice of material parameters is determined based on the patient's age, sex, and health condition, and the database should be updated as more data become available in the digital twin.

E. BIOMECHANICAL MODEL

A simulation model can be automatically created by assigning appropriate material constants and constitutive models from the *material database* to the individual labeled *digital anatomy* structures. Unilateral constraints, such as contact, needle puncture, and friction, as well as bilateral constraints, such as rigid attachments between bodies and sliding or rotating joints, must also be specified here. For the knee, important unilateral constraints are personalized motion axis and friction between femoral cartilage and meniscus. These constraints could be pre-defined but also tuned for each specific patient from the *intraoperative data*.

F. OFFLINE SIMULATION

As discussed in Section IV, and observed from Tables 3, 4 and 5, the highest-performing methods employ an

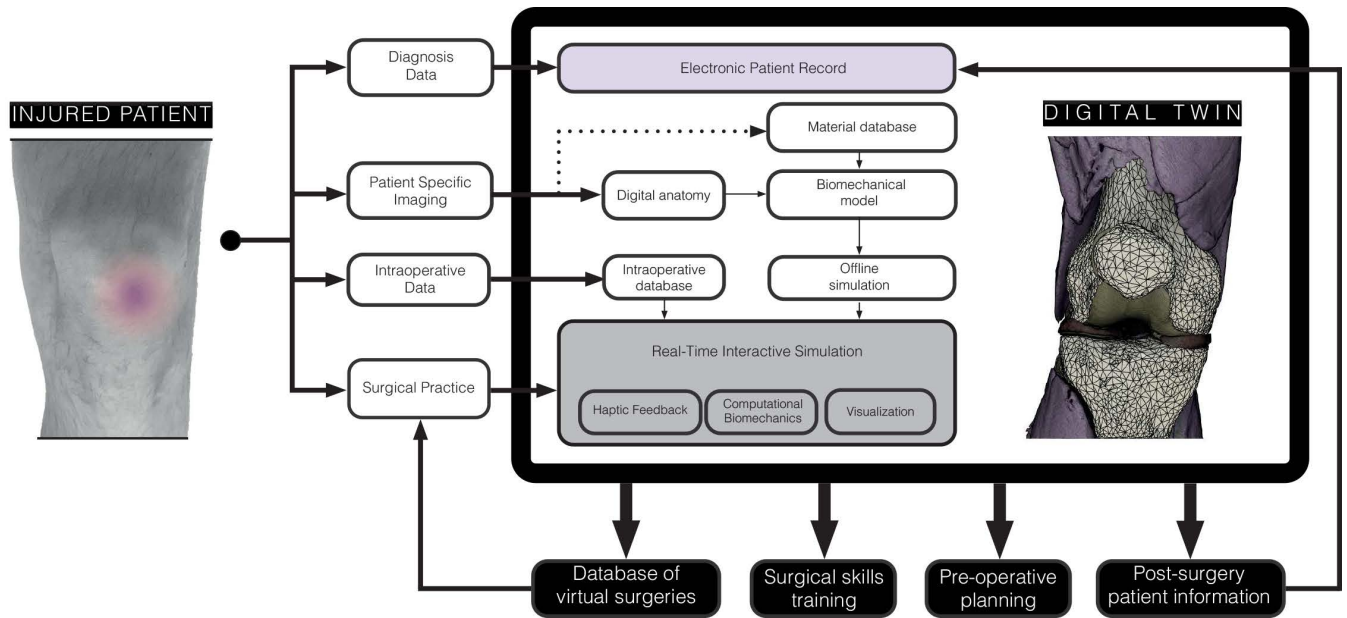


FIGURE 7. Digital twin concept for arthroscopic knee surgery. Arrows indicate flow of information.

offline simulation step to achieve real-time performance. For the TLED approach [91], spatial derivatives, initial element volumes, initial Jacobian, and mass and damping matrices can be precomputed. Model order reduction by proper orthogonal decomposition is performed before the real-time simulation [14]. The Kalman-filter method compute the Kalman gain offline [83]. Thus should offline simulation be included to account for the most complex tissue simulations, or to enable simulation of larger systems.

G. REAL-TIME INTERACTIVE SIMULATION

As shown in Section IV-F, the three threads in interactive real-time simulation are *haptic feedback*, *computational biomechanics* and *visualization*. As shown in Section IV-F, these can be combined using multirate compliant mechanisms.

Considering methods for real-time deformation, as shown in Tables 3, 4 and 5, several methods demonstrate real-time performance of at least a 30 Hz refresh rate. For meshfree methods, it is still difficult to model accurate constitutive behavior, but it is much easier to achieve real-time performance. For mesh-based finite element methods, achieving real-time simulation rates for large models remains difficult. However, corotational formulations, model order reduction, and Kalman filter-accelerated simulations all provide sufficient simulation rates for moderate sized models. Additionally, mesh-based methods have been demonstrated for use in multi-thread architectures with constraint-based interactions and for cutting simulations. Machine learning-based methods are promising in terms of achieving real-time refresh rates, but they require large datasets for training [78]. However, it is likely that we will see further developments in the future.

For haptic feedback, as presented in Section IV-E, recent device developments have focused on novel actuation and transmission methods to improve the performance of active haptic devices. However, validation studies, including medical personnel and case-based simulators, have mostly been performed using commercial haptic devices [142], [143], [148], [150]. Thus, we are most likely yet to observe the impact of these novel methods in surgical simulation. Interestingly, Vaghela *et al.* [150] recently investigated the effect of active versus passive haptic systems in knee arthroscopic surgery by comparing two commercially available arthroscopic simulators: Virtamed ArthroS and Symbionix Arthro Mentor. They invited 38 participants, of whom 13 were experts and 25 were surgeons with a moderate level of experience. The results showed that orthopedic surgeons prefer passive haptic feedback to active feedback in the context of VR arthroscopy. This shows that active systems still have potential for improvement with respect to face validity. However, it should be noted that the active haptic devices in the study were Geomagic Touch devices. Although popular, as highlighted in Section IV-E, this device is located in the low-end-low-cost part of the spectrum of the haptic devices, and it is not unlikely that a higher-fidelity active system could have affected the results.

Visualization has not been included as part of the scope of this review, but remains an important feature. However, many studies have utilized the Chai3D and SOFA frameworks, where a higher-density mesh is used as a slave to the deformation model to achieve a more realistic visual impression [89], [94], [95], [127], [139], [140], [144]. Some studies have also reported implementation in game engines, and some have included head-mounted displays [103], [114], [140], [143].

H. INTRAOPERATIVE DATA

So far discussions have focused on aspects equally relevant for surgery simulators as for a digital twin. However, the introduction of real-time sensor data changes this. As shown in subsection IV-B, novel surgical navigation and force-sensing systems have recently been developed, and the need for sensemaking of the collected data arises. As shown by Ma *et al.* [40], stereo vision fused with IMU-tracking provides virtual rendering of tool position during knee arthroscopy. Synchronizing position data with force data, either from direct or indirect force sensors, can provide sufficient information for storing procedural, haptic and deformable object data in an *intraoperative database*, as well as calibrating haptic interactions.

I. INTRAOPERATIVE DATABASE

Using *intraoperative data* as input, *haptic feedback* in the *real-time interactive simulation* and *material database* can be calibrated from the measured data by pre-training an AI-model. As pointed out by Nazari *et al.* [45], an AI model can estimate haptic information by learning a relationship between applied forces and object deformations. As shown in Section IV-D1, Wu *et al.* [98] used live data to correct a real-time FE simulation during endoscopic surgery. This allows for patient-specific tuning of these parameters. Another application is to provide force feedback in simulation training and during surgery, that is feedback of whether the amount of applied force is suitable (not the same as haptic feedback). Feature extraction techniques using CNNs, as pointed out by Anh *et al.* [12], can prove very useful in this setting. Further studies are needed to explore this potential.

J. SURGICAL PRACTICE

Surgical practice is a set of established methods for treating a specific injury in the context of a specific patient. These methods determine the procedures and tools to be simulated, as well as what is considered good practice. In other fields not covered in this review, such as autonomous ship simulation, good seamanship practice is defined as “(...) *common practice of how to deal with situations that are not explained by rules*” [151]. Similarly, the best surgical practice is an important pillar in designing a meaningful simulation procedure, but also for providing meaningful surgical skill assessment (construct validity). In autonomous ship control algorithms, good seamanship is incorporated together with a path fitness function and safety evaluation as a multi-object optimization problem. A similar mindset could be employed in surgical skill assessment by optimizing a cost function of surgical path precision, interaction force data and best surgical practice. These aspects should be explored further.

K. DIGITAL TWINS IN NEAR- AND FAR FUTURE APPLICATIONS

As introduced in Section II, User Scenarios, and shown in Fig. 7, a digital twin can provide *resident doctor training*,

patient-specific pre-operative planning and a *database of virtual surgeries*. The most common use is likely for the training of resident doctors, as pointed out by Frank [3]. However, we argue that unexplored potentials exist in the other two applications. For example, *patient-specific pre-operative planning* does not have to be constrained by pre-defined procedures. With sufficient fidelity, the digital twin could serve as a simulation environment for the early exploration of novel surgical methods, providing a similar purpose as CAD/CAM/CAE-environments for design engineers. Further, with advancements in AI, it is not unimaginable that this environment could be used to explore a range of surgical procedures to find the best suited or perhaps even a novel method.

Considering the digital twin lifecycle as the lifecycle of a given treatment, *post-operative patient information* should be supplied to the *electronic patient record*. We regard the qualitative data supplied by the surgeon during polyclinic assessment or physical therapist during rehabilitation, as the most realistic means of implementing this. However, self-reporting of pain, swelling and range of motion could also provide this input, as well as through smart rehabilitation devices or sensors not covered in this review.

Finally, if this conceptual digital twin system was realized as envisioned, a database of surgeries, providing detailed transcripts of surgeon actions and patient outcomes, would inevitably follow. This could serve as a research tool and provide new insights into the arthroscopic surgical domain.

VI. DISCUSSION

A. REVIEW

The objectives of our review were to investigate fast and robust design of an arthroscopic digital twin using patient-specific information, and to explore methods for interactive surgical soft tissue simulation for a digital twin, emphasizing speed and accuracy. The search terms, as listed in Table 1, were selected to reflect these objectives. We acknowledge that it is possible that these search terms do not capture all developments in patient-specific imaging, which is reflected in the number of results, but argue that including these findings is important for the overall understanding of the digital twin system.

An important feature of a true digital twin that has not been explicitly addressed in this review is the dynamic behavior of a joint. During knee arthroscopy, the surgeon changes the position of the knee to enable insertion of arthroscopic instruments. Here, internal cavities are opened or closed based on the position of the knee. Modeling the behavior of these cavities is important to fully simulate instrument insertion.

B. DIGITAL TWINS IN CLINICAL PRACTICE?

As presented in this article, a digital twin can have several implications for the training of resident doctors, pre-operative planning, and storage of surgical data. However, there are

several barriers that must be overcome before implementation of such a system could be considered.

Firstly, not all patients with knee injury undergo an MRI scan. Thus, the establishment of a digital twin is thus not possible for these patients. Furthermore, we must be sure that automatic segmentation of anatomical structures does not alter the digital representation of anatomy. Here, work considering explainable AI could contribute to a better understanding and confidence.

As for the use of tool positioning systems and force sensors during manual surgery, this technology is in early development, and challenges related to sterilization procedures and operational costs must be addressed. In addition, the justification of high investment costs for these systems must be discussed in the medical community. Similar to the adoption of other novel technologies, such as robotic surgery, it is likely that the most specialized hospitals could serve as early adopters. Likewise, a thorough discussion in medical communities must determine for which procedures such a system can add sufficient value.

Considering the fidelity of real-time interactive simulation, there is evidence that current surgical simulation systems add value to training of resident doctors given the current state-of-the-art. However, we argue that there is still a need to strive for higher fidelity with respect to computation speed, accuracy, visualization, and haptic feedback, to fully exploit the potentials of the digital twin presented in this article. Moreover, as shown in Fig. 1, we argue that increasing fidelity is necessary to enable the higher hierarchical user-case levels.

As for the implementation of an arthroscopic digital twin in clinical practice, electronic patient records containing patient-specific digital images with supplemental qualitative diagnostic descriptions are already well established in global health care systems. As such, if sufficiently developed and automated, a digital twin could be considered a natural evolution of such a medical record.

C. ETHICAL CONSIDERATIONS

Braun [152] discusses the ethics of digital twins in medicine. Central to his analysis is the view of the digital twin representing the patient, in the sense that it acts on behalf of the physical person. Such representation, it is argued, not only requires informed consent, but also has to remain under the control of the patient.

A complementary perspective is found in the literature on the ethics of electronic patient records (EPR). As introduced, a digital twin is an EPR in the sense that it records information about the patients' state of health. Jacquemard *et al.* [153] makes a scoping review of EPR ethics, identifying five areas of concern, in privacy, autonomy, risk/benefit analysis, human relationships, and responsibility. As such, the use of a digital twin in settings outside the regulations of EPR's, such as for educational or research purposes, must be carefully considered with respect to informed consent and patient data protection.

VII. CONCLUDING REMARKS

In this paper, an arthroscopic digital twin concept was explored in light of the existing scientific literature. A systematic review was conducted following the Preferred Reporting Items for Systematic Review and Meta-Analyses (PRISMA) protocol to summarize the literature from January 2018 to December 2021. This review investigated fast and robust design of an arthroscopic digital twin using patient-specific information, and methods for interactive surgical soft tissue simulation with respect to speed and accuracy. Considering the review findings, a conceptual macro-level arthroscopic digital twin was presented. The review results indicate that interactive surgical soft-tissue simulation is an active field of research, with many recent studies presenting methods for improving computational efficiency and accuracy as well as haptic feedback interaction. However, little work has been conducted on digital twins in the context of arthroscopic surgery. The potential of digital twins should be further explored.

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ØYSTEIN BJELLAND was born in Bergen, Norway, in 1991. He received the M.Sc. degree in mechanical engineering from the Norwegian University of Science and Technology (NTNU), Ålesund, Trondheim, in 2016, where he is currently pursuing the Ph.D. degree in engineering cybernetics. From 2016 to 2020, he worked as a Mechanical Design Engineer at Clara Venture Labs (formerly Prototech), Bergen, developing mechatronic systems for oil and gas industry, fuel cell systems for space applications, and metal additive manufacturing. Since 2020, he has been a Researcher at the Cyber-Physical Systems Laboratory, NTNU. He is also affiliated with the Aalesund Biomechanics Laboratory and TrollLabs. His current research interests include surgery simulation, haptic feedback, and biomechanics. Other research interests include additive manufacturing and engineering didactics.

BISMI RASHEED graduated in civil engineering from the University of Calicut, India, in 2014. She received the M.Tech. degree in computer aided structural analysis and design from the Cochin University of Science and Technology, India, in 2017. She is currently pursuing the Ph.D. degree with the Department of ICT and Natural Sciences, NTNU, Ålesund. She was a Research Scholar with the Department of Applied Mechanics, Indian Institute of Technology Madras, from 2018 to 2020. She is also affiliated with the Cyber-Physical Systems Laboratory, NTNU, and the Ålesund Biomechanics Laboratory. Her research interests include computational modeling, solid mechanics, and biomechanics. Her current research interests include biomechanical characterization, soft tissue deformation modeling, and surgical simulation.

HANS GEORG SCHAATHUN received the cand.mag. degree in mathematics, economics, and informatics, the cand.scient. degree in industrial and applied mathematics and informatics, and the dr.scient. degree in informatics–coding theory from the University of Bergen, Norway, in 1996, 1999, and 2002, respectively. He was a Lecturer in coding and cryptography at the University of Bergen, in 2002, and a Postdoctoral Researcher, from 2003 to 2006. From 2006 to 2010, he was a Lecturer and a Senior Lecturer in computer science at the University of Surrey, U.K. He became a Professor of computing at Ålesund University College, in 2011, which merged into NTNU, in 2016. His research focused on multimedia security, including applications of coding theory and steganalysis using machine learning. His current research interests include artificial intelligence, epistemology, and engineering didactics.



MORTEN D. PEDERSEN received the M.Sc. and Ph.D. degrees in engineering cybernetics from the Norwegian University of Science and Technology (NTNU), Trondheim, Norway, in 2009 and 2017, respectively.

Since 2018, he has been serving as an Associate Professor at the Department of Engineering Cybernetics, NTNU, where he teaches several courses in control systems technology. His research interests include modeling and control of fluid-mechanical systems, pedagogical topics related to the teaching of control theory, biomedical applications of control theory, and the fundamentals of cybernetics.



MARTIN STEINERT was born in Dresden, Germany. He received the B.A., M.A., and Ph.D. (Dr.rer.pol) degrees in technology management from the University of Fribourg, Switzerland. He has been an Assistant Professor with the University of Fribourg, Switzerland, and a Visiting Scholar at MIT and Stanford University, before changing full time to Stanford University as the Deputy Director of the Center for Design Research (CDR) and an Assistant Professor

(Acting) in mechanical engineering. Since 2013, he has been a Full Professor of engineering design at the Department of Mechanical and Industrial Engineering (MTP), Norwegian University of Science and Technology (NTNU). His research interests include fuzzy front end of new product development and design: optimizing the intersection of engineering design thinking and new product development, mechatronics/sensors, and computer sciences (especially machine learning). A special focus is on conceptual development and alpha prototype generation of high-performance requirements and on experimental tools and setups. As of August 2021, he has more than 200 publications registered in Google Scholar. He has several prizes in both teaching and research. He has been a member of the Norwegian Academy of Technological Sciences (NTVA), since 2015.



ALF INGE HELLEVIK received the M.D. and Ph.D. degrees from the Norwegian University of Science and Technology (NTNU), Trondheim, in 2010 and 2018, respectively.

He currently works as an Orthopedic Surgeon at Ålesund General Hospital, where he is the Head of the Aalesund Biomechanics Laboratory. His research interests include Osteoarthritis in hip and knee, and general biomechanics.



ROBIN T. BYE (Senior Member, IEEE) was born in Ålesund, Norway, in 1979. He received the B.Eng., M.Eng.Sc., and Ph.D. degrees (Hons.) in electrical engineering from the University of New South Wales, Sydney, Australia, in 2004, 2005, and 2009, respectively. Since 2008, he has been working at the Department of ICT and Natural Sciences (IIR), Norwegian University of Science and Technology (NTNU), Ålesund, and became a Full Professor, in 2020. At the department, he heads the undergraduate automation engineering programme as well as the Cyber-Physical Systems Laboratory. His research interests include cybernetics, artificial intelligence, neuroengineering, and engineering didactics. He was awarded the Goodeve Medal by The Operational Research Society, in 2019.

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