ÇANKAYA UNIVERSITY

COMPUTER ENGINEERING DEPARTMENT

CENG 407

LITERATURE REVIEW

A Review of the Computer Science Literature Relating to Applying Brain MRI's Into Augmented Reality and Surgical Pre-Planning

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0. Abstract

The use of virtual/mixed reality and patient-specific three-dimensional models in medical education and neurosurgical applications has been rapidly increasing in recent years. In parallel, automated and precise anatomical modeling has become possible thanks to deep learning-based brain MR segmentation. This study reviews the current literature on (3) VR/MR-based anatomy and medical education, (3.1) deep learning-based brain tumor segmentation, and (3.2) the use of patient-specific 3D models in VR/MR environments for neurosurgical planning and patient information; it discusses the strengths and weaknesses of existing studies and reveals the main research gaps in the field.

Keywords: Brain MR, deep learning, segmentation, virtual reality, mixed reality, neurosurgery, medical education, patient-specific model.

1. Introduction

Magnetic Resonance Imaging (MRI) is one of the fundamental diagnostic methods that allows for the non-invasive examination of brain structures with high soft tissue resolution [1]. In clinical practice, MRI data are mostly evaluated as 2D slices, and physicians attempt to understand the 3D anatomical structure and the location of pathological lesions by mentally synthesizing these slices. Especially when dealing with the skull base, deep-seated tumors, and complex vascular pathologies, this mental 3D reconstruction process constitutes a significant cognitive load and becomes a highly experience-dependent process [2], [3].

Similarly, medical education, particularly neurosurgery training, has for many years been conducted through cadaver dissection, 2D atlases, and flat screen images. While these methods provide fundamental anatomical knowledge, they remain limited in understanding complex 3D relationships and patient-specific variations [4]. Although Virtual Reality (VR) and Mixed Reality (MR)-based training applications have been developed in recent years, carrying the potential to increase students' spatial perception and learning motivation [5], a significant portion of these applications are based on standard, idealized anatomical models. Consequently, it is often not fully possible to reflect the anatomical and pathological features specific to a clinical case in the training and planning process.

In this context, automatically generating 3D, patient-specific brain models from 2D MRI slices and interactively visualizing these models in a VR/MR environment presents a significant opportunity for both medical education and neurosurgical operation planning. Deep learning-based segmentation methods allow for the automatic and highly accurate separation of brain tumors and other intracranial structures on MRI [6], [7]; these segmentation outputs can then be converted into 3D surface models through appropriate processing steps. However, the literature reveals that the number of portable systems, focused on education and planning, that combine this AI-based segmentation process within an end-to-end workflow: 2D MRI -> 3D patient-specific model -> VR/MR-based interactive visualization is quite limited [8].

The objective of this study is to create 3D patient-specific models through deep learning-supported automatic segmentation from brain MRI data and to present these models interactively in a virtual/mixed reality environment. The proposed approach is expected to facilitate the process of spatial understanding by reducing the need for mental 3D reconstruction of 2D MRI slices, offer a more realistic and rich learning experience in medical/anatomy education, and provide additional visual support to the clinician during neurosurgical operation planning.

A. Purpose of this Study

The main objective of this study is to develop an integrated system that can automatically create 3D patient-specific models from brain MRI data and present these models interactively within a Virtual/Mixed Reality (VR/MR) environment.

This project addresses a critical gap in current clinical and educational workflows by establishing a single, seamless pipeline from 2D imaging to immersive 3D visualization.

1. **Automated Segmentation:**
   Contribution: Utilizing a deep learning-based method to achieve the automatic segmentation of brain structures and pathological areas from standard 2D MRI slices. This eliminates manual segmentation effort.
2. **3D Model Production:**
   Contribution: Processing the automated segmentation outputs to generate a high-resolution, patient-specific 3D brain model unique to the real patient. This step converts the raw data output into a clinically usable format.
3. **VR/MR Based Interactive visualization:**
   Contribution: Enabling the interactive examination of the 3D model through a portable VR/MR device (like Meta Quest). Interactive tools include rotation, zooming, layer peeling (dissection), and virtual cross-sectioning.
4. **A new approach for Medical Education:**
   New Approach: Provides a novel method for teaching by allowing students to examine complex anatomical relationships in a three-dimensional context using real patient cases.

   Benefit: Overcomes the spatial comprehension limitations inherent in learning brain anatomy from traditional 2D atlases.
5. **Neurosurgical Planning and Patient Information:**
   Planning: Assists the surgeon in achieving a better understanding of the patient-

specific pathology and surrounding structures, facilitating precise surgical approach planning.

Patient Education: Allows the surgeon to demonstrate the procedure to the patient in a more comprehensible and visual manner, improving consent and trust.

B. Expected System Outcomes

The successful development of this system is anticipated to:

- Increase Spatial Comprehension in both educational and clinical settings.
- Support Decision-Making Processes for complex surgeries.
- Reduce the Cognitive Load typically associated with mentally reconstructing 3D anatomy from 2D images.

2. Definitions

Term(s)	**Context**
MRI	Magnetic Resonance Imaging (MRI); a radiological technique used to image soft tissues [1].
Segmentation	The process of classifying pixels in digital images as an anatomical structure or pathology (tumor) [4].
VR	Simulation technology where the user is completely isolated from the external world and immersed in a digital environment [11].
MR(Mixed Reality)	Technology in which virtual objects are overlaid onto the real world image and can be interacted with [19].
Dice Score(DSC)	A similarity coefficient that measures the success of automatic segmentation and takes a value between 0 and 1 [5].
U-Net	A deep learning model developed for biomedical image segmentation, which has a 'U'-shaped architecture [15].
Patient-Specific Model	A personalized 3D structure generated from the patient's own MR/CT data, instead of a standard anatomical atlas [7].

3. Reviewed Applications and Models

Recent systematic reviews demonstrate that VR and AR technologies are increasingly being adopted in anatomy education [1], [2]. A comprehensive meta-analysis by García-Robles et al., examining studies between the years 2000–2024, reports that immersive VR and AR-based anatomy applications significantly increase students' knowledge level and spatial perception [1].

The systematic review by Minouei et al. emphasizes that VR increases medical students' anatomy performance, but stresses that the highest effectiveness emerges when VR is used as a complementary addition to traditional methods [2]. Niu et al., in a study where 3D anatomy models were integrated into a VR-supported blended learning framework, report a significant increase in both examination scores and student satisfaction in the groups using VR [9].

Comprehensive meta-analyses examining the effectiveness of VR/AR across health education in general also report that VR-based training offers positive effects, particularly on skill level, motivation, and self-efficacy [10], [11]. However, a significant portion of these studies used ready-made commercial anatomy applications or general anatomical models, and patient-specific models were rarely addressed.

A. Limitations

The common limitations of the studies in this area are summarized as follows:

- Most studies have small sample sizes and are single-center [1] – [9].
- Long-term knowledge retention and transfer to real clinical performance have been rarely measured [10], [11].
- The VR content used mostly consists of generalized, non-patient-specific anatomy models; the use of personalized brain models based on MR/CT is highly limited.

3.1. Deep Learning-Based Brain MR Segmentation

A. Fully Automated Deep Learning Methods

Brain tumor segmentation is one of the most challenging problems in medical image analysis. Despite this difficulty, deep learning methods have achieved significant success, particularly with large-scale datasets like BraTS (Brain Tumor Segmentation Challenge) [4], [5], [12].

In a review by Liu et al., it was shown that Convolutional Neural Network (CNN)-based models, especially U-Net and its variants, demonstrate performance close to or exceeding manual segmentation, capable of automatically isolating the tumor core, edema, and enhancing regions [4]. A more recent prospective review by Abidin et al. provides a detailed classification of CNN, Transformer, and hybrid models that utilize multi-modal MR (T1, T2, FLAIR, T1ce) and reports that Dice scores have reached the 85–90% range in recent years [5].

Dorfner et al. further show that deep learning is used not only for segmentation but also for tumor classification, distinguishing between recurrence and radionecrosis, and predicting molecular biomarkers (such as IDH, MGMT, etc.) [13]. These studies describe a broader clinical decision support chain where segmentation is used as an initial step.

From Turkey, Çay et al. compared two different deep learning architectures (U-Net and SegNet) demonstrating that U-Net offers higher accuracy and generalizability [9]. Similarly, Abdusalomov et al. reported that an MR-based deep learning model can detect tumor presence and localization with high sensitivity and specificity [14].

B. Semi-Supervised and Data Efficiency Approaches

The most significant problem with fully supervised deep learning methods is their dependence on large labeled datasets that require pixel-level annotation. A semi-supervised review by Jin et al. shows that competitive segmentation performance can be achieved with limited labeled data using techniques such as pseudo-labeling, consistency regularization, GAN-based approaches, and contrastive learning [12]. This presents a significant advantage for real-world clinical centers aiming to produce patient-specific models.

C. Limitations

- Most models operate in off-line, research environments; real-time or VR/MR integration generally remains at a hypothetical level [5] – [13].
- Issues concerning generalizability, robustness, explainability, and regulation (CE/FDA, etc.) for clinical use are still significant barriers.
- The majority of studies focus only on the tumor region; integrated segmentation of vascular structures, functional areas (e.g., motor cortex), and white matter tracts is limited.

3.2. Patient-Specific 3D Models and VR/MR-Based Neurosurgical Applications

A. 3D Printing and Digital 3D Models

Panesar et al. demonstrated that patient-specific 3D printed models offer significant added value for preoperative planning and education, especially for skull base tumors and complex vascular pathologies [7]. The models were used by surgeons to practice surgical approaches, visualize critical structures, and for patient/family education before the operation.

An narrative review by Isikay et al. on patient-specific 3D visualization and "reality technologies" (VR/AR/MR) in skull base neurosurgery emphasizes that these technologies increase spatial awareness in surgical training, planning, and navigation. Furthermore, they contribute to the development of surgical approaches that are respectful of critical neurovascular structures [16].

B. Neurosurgical Planning and Patient Information using VR and MR

Studies on patient-specific VR platforms have shown that both surgical strategy and intraoperative navigation can be improved using 360° VR environments generated from preoperative MR/CT data [17], [20]. These platforms enable the virtual testing of different access routes, the avoidance of risky vascular structures, and even the interactive display of the patient's own anatomy to the patient.

Crispi et al. reported a significant increase in patients' understanding of their disease and their confidence in the treatment decision, in a study where MR-based 3D brain visuals were displayed using mixed reality headsets in addition to routine neurosurgical clinic consultations [19].

Colombo et al. and various other groups have reported that mixed reality provides advantages in terms of ergonomics and intuitive understanding compared to classic 2D imaging and classic navigation in cranial neurosurgical planning for tasks such as surgical corridor selection, determining the craniotomy site, and staying clear of vascular structures [18], [20].

Furthermore, studies such as planning patient-specific reconstruction plates using mixed reality systems [19] and AR navigation for arteriovenous malformation surgery [20] also indicate the potential of these technologies to reduce surgical time and error.

3.3. Evaluation Criteria Used In Existing Studies

The studies reviewed in the literature utilize different evaluation metrics according to three main research axes: (A) deep learning-based MRI segmentation, (B) VR/MR-based medical education applications, and (C) the clinical accuracy of patient-specific 3D models and VR-supported surgical planning. This section summarizes the criteria by which the success of the studies in the field is evaluated and highlights the methodological differences between the research areas.

A. Metrics Used in Deep Learning-Based MRI Segmentation Studies

In segmentation research aiming for the automatic extraction of tumors or anatomical structures from MR images, quantitative metrics are widely used to measure accuracy.

- **Dice Similarity Coefficient (DSC):** It is the most commonly used metric to measure segmentation accuracy. It takes a value between 0 and 1, where 1 indicates ideal agreement.
- **Intersection over Union (IoU / Jaccard Index):** It measures the ratio of intersection to union between the predicted region and the ground truth annotation.
- **Sensitivity / Recall:** Indicates how well the model can capture positive classes such as a tumor.
- **Specificity:** Evaluates whether normal tissue is correctly preserved without false positive classification.

- **Hausdorff Distance (HD95):** Measures how close the segmentation boundaries are to the true boundary; this is especially important in preparation for surgery.
- **Voxel-wise Accuracy:** Gives the rate of correct classification for every single pixel; it summarizes the global accuracy.

These metrics establish a common language for comparing deep learning models; furthermore, they allow for the detailed analysis of performance across sub-structures such as the brain tumor, edema, or the contrast-enhancing region.

B. Metrics Used in VR/MR-Based Medical Education Studies

VR/MR-based educational research is mostly evaluated through learning outcomes, user experience, and performance improvement.

- **Student achievement scores (pre-test / post-test):** This is the fundamental criterion used to measure the effect of VR training on knowledge gain.
- **Spatial awareness scales**: Measures the student's level of understanding of 3D relationships.
- **System Usability Scale (SUS):** Evaluates the user experience of the VR application in terms of accessibility, usability, and ergonomics.
- **Self-efficacy and satisfaction surveys:** Measures the student's self-confidence, motivation, and attitude toward the application.
- **Task completion time:** Indicates how efficiently the participant can complete a specific clinical task within the VR environment.

These criteria are used to objectively compare how VR/MR-supported education affects learning performance compared to traditional methods.

C. Metrics Used in Studies on Patient-Specific 3D Models and VR-Supported Neurosurgical Planning

Patient-specific models used in surgical planning are evaluated not only as a visual tool but also in terms of measurable clinical outcomes.

- **Anatomical Accuracy (measurement error – mm):** Evaluates the difference between the produced 3D model and the true anatomical structure; this is of critical importance in skull base surgery.
- **Reduction in surgical time:** The contribution of VR-supported planning to the duration of the operation is measured.
- **Planning Accuracy:** The accuracy of the approach chosen by the surgeon, the craniotomy site, and the navigation path is evaluated.
- **Error rate / Deviation from critical structures:** Shows whether model-supported planning reduces risks.

- **Surgeon satisfaction and ease of use:** This is one of the most critical subjective metrics that determines clinical applicability.

These criteria are used to demonstrate the aspects in which VR/MR-based surgical planning and patient communication approaches provide an advantage compared to traditional 2D image review methods.

4. General Assessment and Synthesis of the Literature

When the reviewed literature is evaluated from a holistic perspective, it is clear that VR/MR-based medical education leads to a significant increase in student learning and spatial awareness; deep learning models achieve high accuracy levels in brain tumor segmentation; and patient-specific 3D models offer valuable contributions to both surgical planning and patient information processes. However, a noticeable point is that these three research areas are progressing largely independently of one another. Most VR applications use standard and idealized anatomical models, while deep learning-based segmentation studies primarily focus only on technical accuracy metrics; and integrated system studies focusing on the interactive use of 3D patient-specific models in VR/MR environments remain highly limited.

Therefore, a critical gap still exists in the literature:

"2D MRI → Automated segmentation → 3D patient-specific model → Interactive VR/MR inspection" The lack of a platform where the steps are combined end-to-end, and which is usable for both education and surgical planning.

This study aims to fill this gap, both in terms of research and application, through its approach that synthesizes three different axes of the field and brings together methods previously addressed separately in the literature within a single workflow.

5. Literature Comparison and Review

Work(Ref)	**Used Technology**	**Focus Area**	**Patient Related Data?**	**Main Restrictions and Limitations**
García-Robles et al. [1]	Immersive VR/AR	Anatomy Education	**No** (General Model)	Doesn't contain models for an individual.
Liu et al. [6]	Deep learning via CNN	Tumor Detection	**Yes** (Dataset)	Only has the segmentation feature but lacks implementation into reality.
Panesar et al. [11]	3D Print	Surgical Pre-plan	**Yes**	Static Model; can't be readjusted after operation(s).
Crispi et al. [12]	Mixed Reality	Inform Patient	**Yes**	The automated segmentation workflow is not fully integrated; there is a manuel process.
Proposed Project	DL + VR/MR	Education & Surgical Pre-plan	**Yes** (Automatic)	Fulfills every limited aspect with a reliable base.

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