ADVANCED MIXED REALITY AND STEREOSCOPIC 3D RECONSTRUCTION PROTOCOL FOR PREOPERATIVE PLANNING IN NEURO-ONCOLOGY: A STANDARDIZED OPTIMIZATION WORKFLOW

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ABSTRACT

Background: Traditional neurosurgical planning based on two-dimensional (2D) magnetic resonance imaging (MRI) slices requires complex cognitive three-dimensional (3D) translation. This paradigm introduces inter-observer variability and potential boundary inaccuracies during complex skull-base and neuro-oncological resections. Mixed Reality (MR) spatial computing offers 1:1 stereoscopic holographic overlays, but direct clinical implementation is restricted by computational limits and latency of standalone head-mounted displays (HMDs).

Objective: To develop and validate an optimization protocol that transforms raw multi-modal DICOM imaging datasets into high-fidelity, real-time rendering 3D polygonal meshes optimized for intraoperative holographic navigation.

Methods: A prospective technical validation study was performed on 45 patients with complex cranial tumors. High-resolution isotropic DICOM datasets (≤1mm slices) underwent multi-modal coregistration and semi-automated segmentation. Initial high-density meshes generated by marching cubes algorithms were processed via quadric error metrics decimation, Laplacian surface smoothing, and manifold correction. Geometric accuracy was evaluated intraoperatively before dural opening using a sterile optical surface scanner to measure the Root-Mean-Square Error (RMSE) between the virtual holographic surface and physical anatomy.

Results: The optimization workflow achieved a mean global polygon reduction of 79.1% across all segmented layers (cerebral cortex, vascular tree, tumor volume, ventricles) without anatomical degradation. Hardware rendering efficiency locked at a maximum threshold of ≥90 frames per second (FPS), completely eliminating latency. Quantitative point-cloud analysis demonstrated a mean spatial deviation (RMSE) of 0.84 ± 0.19 mm, well within the sub-millimeter clinical safety window.

Conclusion: This standardized workflow provides a geometrically accurate, computationally stable bridge between radiological data and mixed reality platforms. It effectively eliminates spatial misinterpretation, establishing a robust scientific framework for advanced preoperative planning, intraoperative navigation, and open-access neurosurgical education.

Keywords: *Mixed Reality; Spatial Computing; Three-Dimensional Reconstruction; Preoperative Planning; Neurosurgery; DICOM Optimization.*

INTRODUCTION

The optimal resection of complex intracranial tumors requires a precise understanding of specialized spatial relationships between the lesion margin, adjacent eloquent cortical areas, and critical white matter tracts [1,2]. Traditional surgical planning utilizes multi-planar reconstructions provided by computed tomography (CT) and magnetic resonance imaging (MRI) [3]. Although these modalities offer superb diagnostic detail, they present data

on flat, two-dimensional screens. The neurosurgeon must perform a continuous cognitive reconstruction to translate 2D data into a 3D intraoperative field [4]. This translation introduces operator-dependent structural bias and spatial uncertainty, especially near intricate deep skull base corridors [5].

The introduction of neuronavigation systems significantly modified modern neurosurgery by providing stereotactic tracking [6]. However, standard platforms still suffer from the "screen-to-field" disconnect, where the surgeon must look away from the physical patient to verify trajectories on an external monitor [7]. Mixed Reality (MR) technologies and spatial computing resolve this barrier by superimposing interactive, 1:1 scale stereoscopic holograms directly onto the physical environment through Optical See-Through Head-Mounted Displays (OST-HMDs) [8,9]. This allows the surgical operator to maintain visual focus on the patient while simultaneously visualizing deep intracranial volumes in real-time [10].

Despite these clinical benefits, direct deployment of clinical DICOM (Digital Imaging and Communications in Medicine) datasets onto modern mobile HMD chipsets is computationally prohibitive [11]. Raw clinical segmentations contain millions of dense, unoptimized polygons with extensive topological artifacts [12]. Attempting to render these datasets raw leads to hardware saturation, causing frame-rate drops below 30 frames per second (FPS), display stuttering, and severe simulator sickness due to vestibulocular mismatch [13,14]. Consequently, establishing a rigorous mathematical optimization pipeline that balances geometric fidelity with rendering stability is mandatory [15]. This study describes and validates a standardized mesh optimization workflow that bridges the gap between high-volume radiological data and real-time mixed reality navigation, under the scientific principles of the Neurocirugía Bajo 0 Grados research paradigm.

METHODS

Patient Selection and Imaging Protocol

A prospective cohort of 45 patients with complex neuro-oncological lesions (including skull base meningiomas, high-grade gliomas near eloquent areas, and deep-seated lesions) was selected for protocol validation. Thin-slice acquisitions were performed using a 3.0-Tesla MRI scanner and a 64-slice CT scanner to ensure isotropic voxel values. Sequences included post-contrast T1-weighted magnetization-prepared rapid gradient-echo (3D MP-RAGE) with a slice thickness $t = 0.9$ mm, T2-weighted fluid-attenuated inversion recovery (FLAIR) at a slice thickness $t = 1.0$ mm, and CT angiography at $t = 0.625$ mm for vascular coregistration.

Segmentation and Volumetric Fusion

Raw datasets were imported into a specialized medical imaging workstation. Multi-modal coregistration was achieved via a normalized mutual information algorithm, ensuring structural alignment between MRI and CT coordinate matrices [16]. Semi-automated, region-growing and threshold-based segmentations were systematically conducted to generate independent volumetric binary masks for four key structures: the cerebral cortex, the ventricular system, the primary lesion boundary, and the surrounding arterial and venous trees.

Polygonal Optimization Pipeline

Surface meshes extracted from binary masks using standard marching cubes presented a high polygon count ($P > 2.5 \times 10^6$ triangles), which is unsustainable for mobile rendering. The following optimization pipeline was applied:

1. *Quadric Error Metrics Decimation:* Controlled simplification was executed by iterative edge-collapse contractions [17]. The structural contraction error was managed by a quadric error matrix Q to minimize geometric distance changes from the original surface, targeting an overall 75%-80% decimation rate.

2. *Laplacian Surface Smoothing:* Voxel-step artifacts were corrected using a non-degenerative Laplacian smoothing filter. Vertex coordinates v_i were adjusted based on their adjacent topological neighbors v_j:

$$v_i^{new} = v_i + \lambda \sum w_{ij} (v_j - v_i)$$

where λ represents the dampening constant ($\lambda = 0.5$) and w_{ij} is the normalized spatial weight factor, ensuring surface smoothing without causing volume loss in critical tumor margins [18].

3. *Manifold Repair:* Topologies were checked for non-manifold edges, self-intersections, and open boundaries. Small boundary holes ($\leq 5\ mm^2$) were filled using progressive triangulation algorithms, and normal vectors were recalculated to establish uniform specular shading.

Intraoperative Accuracy Assessment

Optimized meshes were compiled into a custom graphic engine running on a standalone HoloLens 2 device. Intraoperatively, prior to dural incision to prevent brain shift bias, a high-resolution sterile optical scanner mapped the bone flap and exposed cortical surface contours [19]. A 5,000-point cloud was registered against the holographic coordinates. Spatial accuracy was defined by computing the Root-Mean-Square Error (RMSE) between the virtual mesh surface (S_v) and the physical scanned surface (S_p):

$$RMSE = \sqrt{ [(1 / N) \sum || p_{(k,v)} - p_{(k,p)} ||^2]}$$

RESULTS

The optimization pipeline successfully processed all 45 cases. Quantitative mesh simplification parameters and computational processing details are presented in Table 1.

Table 1. Mesh Simplification Parameters and Computational Performance Metrics.

ANATOMICAL LAYER	INITIAL TRIANGLES	OPTIMIZED TRIANGLES	REDUCTION RATIO	PROCESSING TIME (MIN)	HMD STABILITY
Cerebral Cortex	1,845,210	369,042	80.0%	14.2 ± 2.1	Locked (≥ 90 FPS)
Tumor Volume	421,900	92,818	78.0%	8.5 ± 1.4	Locked (≥ 90 FPS)
Vascular Tree	984,310	226,391	77.0%	19.1 ± 3.3	Locked (≥ 90 FPS)
Ventricular System	312,450	56,241	82.0%	6.2 ± 0.9	Locked (≥ 90 FPS)

The raw multi-layered mesh generated a combined average of 3,563,870 triangles per patient, reducing mobile HMD refresh rates to an unstable ***12 ± 4*** FPS. Following optimization, the average total triangle count dropped to 744,492, a global reduction of 79.1%. This allowed the standalone device to maintain a locked frame rate of 90.0 FPS with zero visible latency during rapid rotation or spatial multi-planar cutting plane clipping. Point-cloud validation demonstrated high geometric fidelity, showing a mean overall RMSE of ***0.84 ± 0.19*** mm (range: 0.52 to 1.24 mm). The total procedural workflow time was ***48.0 ± 7.7*** minutes, proving highly compatible with clinical surgical timelines.

DISCUSSION

The integration of Mixed Reality within neurosurgical workflows represents a substantial improvement over standard visualization techniques [20]. This study establishes that extensive polygon decimation (up to 82%) can be performed safely while fully maintaining sub-millimeter geometric precision (***0.84 ± 0.19*** mm). By minimizing the overall polygon overhead, the rendering engine avoids performance drops, locking execution at 90 FPS. This performance level is essential for preventing visual latency and vestibulocular discomfort during stereoscopic holographic interactions [14].

Previous virtual and augmented reality protocols often faced an optimization imbalance [11]. Standard decimation algorithms can smooth out critical surgical details, such as small vascular branches or fine tumor boundaries near the skull base [12]. Our protocol utilizes Quadric Error Metrics, which weights edge collapses based on local surface curvature. This mathematical approach preserves sharp geometric borders, protecting structural margins as confirmed by our low intraoperative surface deviation (0.84 mm). This performance satisfies the stringent safety requirements of modern microneurosurgery [6].

Beyond intraoperative guidance, this validated optimization workflow serves as a technical foundation for digital medical education, such as the initiatives led by the Neurocirugía Bajo 0 Grados platform. Providing high-fidelity, computationally optimized 3D anatomical models allows for the global dissemination of complex neurosurgical paths [8]. Medical students and residents can interact with real surgical cases in an immersive virtual format, practicing safe approach tracks and enhancing spatial anatomy comprehension without patient risk [4]. A

primary limitation of this study is that it relies on static preoperative imaging. It does not dynamically account for "brain shift"—the mechanical deformation of the cerebrum following dural opening and CSF loss [19]. Ongoing research will focus on integrating real-time intraoperative ultrasound data into the MR engine to adaptively update the optimized meshes during surgery.

CONCLUSION

This study validates a reproducible optimization pipeline for displaying multi-modal neurosurgical models within standalone Mixed Reality platforms. By achieving an average 79% reduction in polygon counts while maintaining sub-millimeter geometric accuracy (0.84 mm), this protocol addresses the hardware limitations of mobile spatial computing. This standardized workflow provides a secure methodology for advanced preoperative simulation, complex neuro-oncological mapping, and open-access neurosurgical education worldwide.

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