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Review

CNC-Inspired Robotic Hair Cutting: A Comprehensive Survey on Precision Personal Care Automation

Ameer Tamoor Khan [1] and Shuai Li [2,*]

[1] Department of Plant and Environmental Sciences, University of Copenhagen, DK-1165 Copenhagen, Denmark
[2] Faculty of Information Technology and Electrical Engineering, University of Oulu, FI-90014 Oulu, Finland
* Correspondence: shuai.li@oulu.fi

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Abstract: The development of haircutting robots has gained significant attention for applications in personal grooming and healthcare, driven by population aging, labor shortages, and increased demand for contactless interaction. Existing efforts, however, remain fragmented, addressing perception, hair modeling, or motion planning in isolation without a systematic framework. This survey provides a comprehensive review of robotic haircutting through the lens of Computer Numerical Control (CNC) machining principles, proposing a unified framework that treats hair manipulation with industrial manufacturing rigor. We systematically analyze the field across five key dimensions: system architectures including gantry-based, manipulator-based, and hybrid configurations; sensing modalities encompassing vision, force, proximity, and tactile feedback; hair modeling techniques from physics-based simulation to neural reconstruction methods; toolpath planning strategies adapted from CNC machining including coverage planning and multi-pass optimization; and control approaches for precision execution and safety assurance. We present detailed comparisons of existing prototypes and commercial systems, identify key technical challenges including head motion compensation, hair property variability, and safety-critical control, and outline promising research directions. This survey bridges the gap between service robotics and precision manufacturing, providing researchers with a structured foundation for advancing haircutting robot technology toward practical deployment.

Keywords: robotic hair cutting; CNC-inspired automation; coverage path planning; precision control; personal care robotics; human-robot interaction

1. Introduction

Population aging, labor shortages in service industries, and the interest in contactless interaction have increased demand for automation in personal grooming, especially after COVID-19 [1]. Within this context, haircutting robots have been regarded as a new frontier of service robotics, aiming to deliver accessible, hygienic, and consistent grooming while reducing the physical burden on human stylists. Recent comprehensive treatments of this emerging field can be found in [2–4].

The hairstyling industry represents a massive global market exceeding $50 billion annually, yet remains almost entirely manual despite revolutionary advances in robotics and automation. While industrial robotics has transformed manufacturing through precise, repeatable operations, personal care services like hair cutting have resisted automation due to fundamental technical barriers: the complexity of hair as a deformable material [5], safety requirements for close human-robot interaction [6], and aesthetic demands requiring adaptive decision-making.

To better understand this emerging application, it is instructive to relate haircutting to other service robots that already perform coverage-oriented tasks. A direct analogy can be drawn between robotic lawn mowing and robotic haircutting: both require the robot to systematically traverse a target domain and remove material to a prescribed level. The similarity motivates technology transfer from mature service robots to haircutting. However, haircutting exhibits unique characteristics that distinguish it from conventional coverage tasks. The workspace is a human head with sensitive anatomy and strict safety requirements. The manipulated medium is deformable and diverse across users, varying in texture, density, curl pattern, and moisture content [7,8]. Furthermore, the outcome is judged not only by geometric completeness but also by aesthetic quality and personalization.

This survey proposes reconceptualizing robotic hair cutting through Computer Numerical Control (CNC) machining principles, treating hair manipulation with precision manufacturing rigor. CNC machining revolutionized manufacturing by enabling unprecedented precision, repeatability, and automation in material processing [9]. When we observe 5-axis CNC machining, particularly operations sculpting complex 3D surfaces, striking parallels emerge with hair cutting requirements. Both demand precise multi-axis tool positioning, continuous trajectory control, real-time adaptation to material properties, and sophisticated path planning optimizing coverage and finish quality. In typical 5-axis CNC systems, the rotational and linear axes follow hierarchical coordination where the linear axes (X, Y, Z) provide primary positioning while rotational axes (A, B, or C) adjust tool orientation. However, in our proposed haircutting system illustrated in Figure 1, we employ synchronized parallel control of all five axes to enable continuous contouring motion around the complex curved geometry of the human head, similar to 5-axis simultaneous machining operations. This coordination strategy allows the cutting tool to maintain optimal orientation relative to the scalp surface throughout the entire trajectory, maximizing both cutting efficiency and safety margins.

While the CNC analogy provides a powerful framework for systematic automation, it is essential to recognize that haircutting introduces fundamental challenges that extend beyond traditional CNC machining paradigms. Unlike rigid workpieces in conventional CNC operations, hair is a highly deformable material that responds dynamically to cutting forces, exhibits significant inter-individual variability in mechanical properties, and requires aesthetic evaluation criteria that transcend purely geometric specifications. The safety-critical nature of operating in close proximity to sensitive human anatomy demands control strategies with guaranteed collision avoidance and compliant interaction capabilities not typically required in industrial machining. Most importantly, the aesthetic dimension of haircutting, encompassing style preferences, facial symmetry considerations, and subjective quality judgments, cannot be fully captured by geometric precision metrics alone. Therefore, our CNC-inspired framework must be augmented with advanced sensing for material property adaptation, learning-based approaches for aesthetic evaluation, and human-centered design principles for safe interaction. These extensions transform the CNC paradigm from a pure precision manufacturing model into a hybrid framework that combines industrial rigor with the adaptive intelligence required for personalized service robotics.

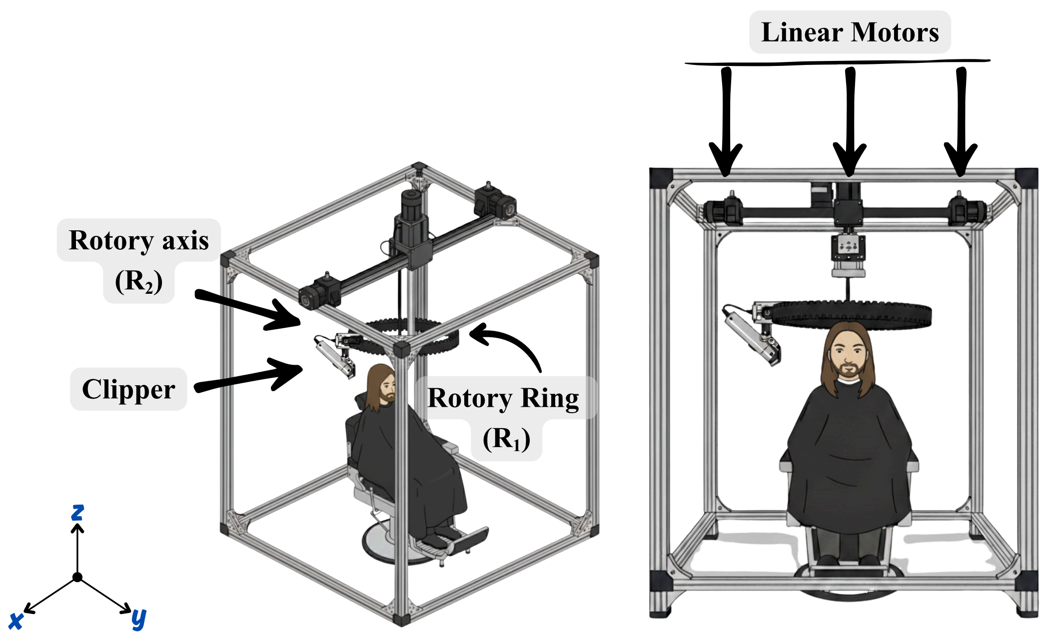

Figure 1. CNC-inspired 5-axis robotic hair cutting system architecture showing aluminum extrusion gantry frame with XYZ linear motion, rotary positioning ring (R_1), tool head with clipper and tilt rotation (R_2), and integrated sensing.

The mobile robotics community has developed a well-recognized structure for autonomy, usually described in terms of three canonical problems: localization ("Where am I?"), coverage planning ("Where to go?"), and control ("How can I go there?"). This structure has guided progress in domains ranging from autonomous vehicles to household service robots [10,11]. We adopt this framework to systematically analyze haircutting robots, as illustrated in Figure 2.

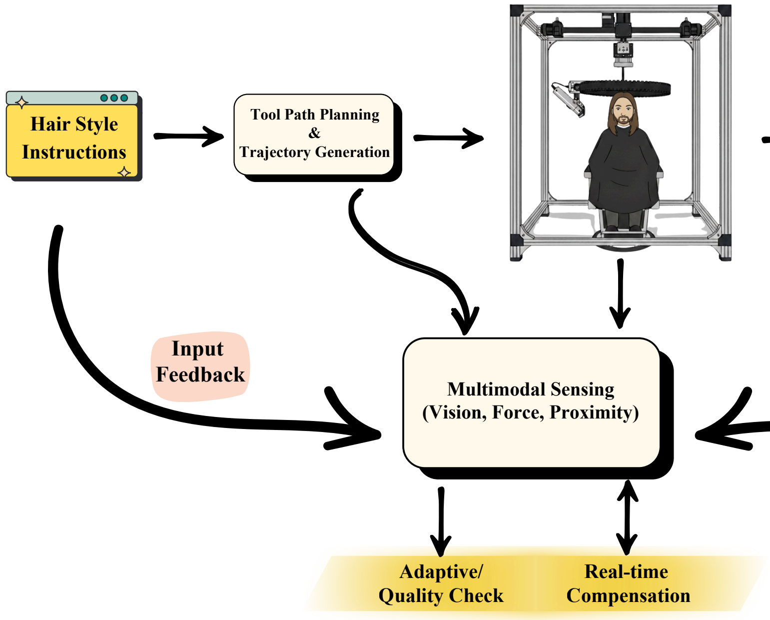

Figure 2. Block diagram of the CNC-based robotic hair-cutting workflow, showing input hairstyle specifications, toolpath generation, multimodal sensing feedback, adaptive correction, and final precision cutting execution.

The remainder of this survey is organized as follows. Section 2 reviews related work and existing haircutting robot prototypes. Section 3 examines system architectures and hardware configurations. Section 4 surveys sensing modalities for localization and perception. Section 5 analyzes hair modeling techniques. Section 6 presents toolpath planning and coverage strategies. Section 7 discusses control approaches and safety mechanisms. Section 8 identifies open challenges and future directions. Section 9 concludes the survey.

2. Related Work and Existing Systems

Attempts at robotic haircutting are relatively recent and remain fragmented. Early concepts appeared in patents for automatic haircutting machines [12], followed decades later by DIY prototypes demonstrating feasibility but lacking systematic autonomy. The field has evolved through several generations of systems, each addressing different aspects of the haircutting challenge with varying degrees of sophistication. Recent surveys provide comprehensive overviews of this emerging domain [3].

Shane Wighton's depth-camera-guided haircutting arm [13] and the "Stuff Made Here" UR5e-based robot [14] demonstrated feasibility but lacked systematic autonomy. Commercial efforts have included Panasonic's shampoo and head-massage robot [15] and more recent patented haircutting devices [16]. Academic research has explored more principled approaches, including the University of Tokyo's strand-oriented styling robot [17], MIT's RoboWig with tactile and visual sensing [18], and Moe-Hair's soft end-effectors for compliant manipulation [19,20]. Related work on robotic combing and brushing further emphasizes safe, contact-rich interaction [21]. Table 1 provides a detailed comparison of existing haircutting robot systems and prototypes, organized by primary task focus to facilitate meaningful comparisons.

Haircutting robots benefit from mature experience in several related domains. Domestic service robots such as vacuum cleaners, exemplified by the iRobot Roomba [22], evolved from wall-following and bump sensing to visual SLAM and decomposition-based coverage. Robotic lawn mowers, such as the Husqvarna Automower [23], incorporated GPS and outdoor navigation techniques. These coverage-oriented systems provide templates for systematic trimming operations that can be adapted to the haircutting context. For example, the Roomba 980 model demonstrated the effectiveness of vSLAM (visual Simultaneous Localization and Mapping) for systematic room coverage with 95% area coverage efficiency in controlled environments. Similarly, the Automower 450X achieves boundary-following accuracy within ±2 cm using GPS-assisted navigation combined with boundary wire detection. These quantitative benchmarks from mature service robotics domains provide concrete performance targets that can guide haircutting robot development, particularly for achieving systematic scalp coverage with minimal redundancy.

Surgical robotics provides another valuable source of technology transfer. Precise localization and constrained trajectory generation, exemplified by the da Vinci system [24], enable safe operation in anatomically sensitive environments. The emphasis on safety-critical control directly applies to haircutting near sensitive facial regions, where even minor errors could result in injury or aesthetic defects [4]. The da Vinci surgical system achieves positioning accuracy of 0.1–0.2 mm with force feedback sensitivity below 0.1 N, demonstrating the level of precision and safety achievable in human-contact applications. These specifications establish performance benchmarks directly applicable to haircutting robots operating near sensitive facial anatomy, where similar precision and force sensitivity are essential for preventing accidental contact with ears, eyes, and scalp.

Computer numerical control has long relied on multi-pass toolpath planning [9], directly paralleling recursive material removal in haircutting. CAM software generates optimized trajectories for complex 3D surfaces, providing algorithmic foundations for hair cutting path planning that can handle the curved geometry of the human head while optimizing for coverage efficiency and cut quality. The theoretical foundations for translating CNC principles to haircutting have been established in [2].

Table 1. Comparison of existing haircutting robot systems and prototypes. systems are grouped by primary task focus to facilitate meaningful comparisons within each category.

System/Approach	Platform Type	Sensing	Planning Method	Task Focus	Key Limitations
Cutting-Focused Systems					
Gronier (1966) [12]	Automated device	Mechanical	Fixed patterns	Basic cutting	Early patent, no sensing
Wighton (2020) [13]	Custom scissor arm	Depth camera	Heuristic trajectory	Cutting demo	DIY prototype, no systematic autonomy
Stuff Made Here (2021) [14]	UR5e manipulator	RGB-D camera	Pre-programmed paths	Entertainment	Single style, lacks safety guarantees
Aldabbah (2023) [16]	Patented device	Not specified	Automated paths	Full haircut	Patent only, no validation
Front hair styling (2025) [17]	Custom system	Vision-based	Path planning	Strand adjustment	Limited to front hair
Hair Manipulation Systems					
RoboWig (2022) [18]	Robotic arm	Visual + tactile	Learning-based	Hair brushing	Not cutting; limited generalization
Hair combing (2021) [21]	General-purpose arm	Visual + force	Reactive control	Combing task	Simple trajectories only
Moe-Hair (2024) [19]	Soft end-effector	Force/tactile	Compliant control	Hair manipulation	No cutting capability
Scalp Care Systems					
Panasonic (2012) [15]	Custom robot	Pressure sensors	Fixed patterns	Shampoo	No cutting, limited to scalp care
CNC-inspired (Proposed)	5-axis gantry	Multimodal	CAM-based toolpath	Full haircut	Requires validation

3. System Architectures

Haircutting robot architectures can be categorized into four main configurations, each presenting distinct trade-offs between workspace coverage, precision, and system complexity. Table 2 summarizes these architectural options and their key characteristics.

Table 2. Comparison of robot architecture configurations.

Architecture	Workspace	Precision	Complexity *
Gantry (CNC-style)	Full head	<0.5mm	Medium **
Serial manipulator	Limited	1–2mm	High ***
Parallel (Stewart)	Partial	<0.3mm	High ***
Hybrid systems	Full head	0.5–1mm	Very high ****

* Complexity ratings: ** = 3–5 DOF with standard controllers; *** = 6+ DOF or complex kinematics requiring advanced control; **** = Multiple coordinated subsystems with hierarchical control

Gantry-based systems, inspired by CNC mills, employ Cartesian gantries providing XYZ positioning with rotary axes for orientation control. As shown in Figure 1, a rotary ring (R_1) enables circumferential tool positioning around the head, while a tilt axis (R_2) provides tool orientation adjustment. Aluminum extrusion frames offer high stiffness-to-weight ratios, minimizing deflections during motion. This configuration provides full spatial positioning capability with sub-millimeter precision, making it particularly well-suited for systematic coverage of the entire head surface.

A critical challenge in all architectural configurations is accommodating natural head motion during extended haircutting procedures. Gantry systems, while offering superior precision in static scenarios, require active compensation mechanisms when the head moves, as their large inertia limits dynamic response. Serial manipulators provide greater adaptability to head motion through their inherent flexibility, but may sacrifice precision in certain joint configurations. Parallel mechanisms offer excellent dynamic response and precision but with limited workspace coverage. Hybrid systems can theoretically combine the advantages of multiple architectures, using a gantry for gross positioning and a parallel mechanism for fine tracking, but at the cost of significantly increased mechanical and control complexity. The selection of architecture must therefore consider not only static precision metrics but also the system's ability to maintain safe and accurate operation under the dynamic conditions of real-world human-robot interaction.

Serial manipulator systems utilize industrial manipulators such as the UR5e to provide flexibility and established control frameworks. However, they face kinematic constraints when operating around spherical head geometry, with singularities and joint limits forcing suboptimal tool orientations in certain regions of the workspace. Parallel mechanisms, including Stewart platforms and similar parallel kinematic machines, offer exceptional precision and stiffness within limited workspaces, making them potentially suitable as secondary positioning stages for fine finishing operations.

Hybrid configurations combine serial and parallel mechanisms, or gantry systems with articulated end-effectors, to provide both workspace coverage and local precision. While these systems offer the most comprehensive capability, they also introduce the greatest mechanical and control complexity.

End-effectors for haircutting robots must accommodate multiple tools and provide integrated sensing capabilities. Electric clippers for bulk removal operate through oscillating blade motion at 3000–6000 RPM, while scissors provide precision cutting for detail work and thinning shears enable texture control. Quick-change interfaces allow tool switching during operation to accommodate different cutting phases.

Integrated sensing at the end-effector includes force/torque sensors mounted at the tool interface to monitor cutting resistance, proximity sensors for collision avoidance, and tactile arrays to estimate hair density and properties during contact. Compliance mechanisms such as series elastic actuators (SEA) and variable stiffness actuators (VSA) provide compliant interaction, enabling safe contact with the scalp while maintaining cutting precision [25].

4. Sensing and Localization

Localization is essential for haircutting robots, enabling trajectory planning and safe interaction. Following the mobile robotics perspective, the core problem is estimating the clipper-head pose reliably under human motion and complex hair geometry. Table 3 provides a systematic overview of sensor categories and their roles in haircutting robots.

Table 3. Sensor categories and their roles in haircutting robots.

Category	Representative Types	Key Role in Haircutting
Proximity/Range	Ultrasonic, Infrared, Capacitive, mmWave radar	Collision avoidance, scalp distance monitoring, user safety
Active Depth	Structured light (Kinect, RealSense), ToF cameras, 2D/3D LiDAR	Accurate head geometry reconstruction, initialization of trimming models
Vision	RGB cameras, Stereo vision, RGB-D, Event cameras	Head pose estimation, hairstyle recognition, robust tracking under motion
Proprioceptive	Joint encoders, IMUs, Joint torque sensors	Precise end-effector motion estimation, stable kinematic constraints
Contact/Tactile	Force sensors (6-axis F/T), Tactile arrays, Electronic skin	Real-time scalp contact feedback, compliant motion control

Following mobile robotics principles, localization can be organized into three levels. Global localization establishes absolute pose in a consistent coordinate frame. Outside-in vision with fixed cameras or RGB-D sensors offers reliable initialization [26], either through fiducial markers such as AprilTags [27,28] or markerless head modeling based on 3D morphable models [29]. External tracking systems including motion capture, magnetic tracking, or UWB beacons provide high-accuracy alternatives when infrastructure permits [30].

Relative localization focuses on incremental motion tracking without external infrastructure. Visual odometry [31,32], optical flow [33], and visual-inertial odometry provide lightweight solutions but suffer from occlusion in dense hair regions. Proprioceptive sensing with IMUs [34] and encoders enables continuous updates, though drift accumulates over time without periodic correction.

Integrated fusion combines global stability with local responsiveness. Filtering-based methods including Kalman filters [35], extended Kalman filters [36], unscented Kalman filters [37], and particle filters [38] handle sensor noise in real time. Optimization-based approaches such as factor graph optimization [39] and sliding-window estimators achieve long-horizon consistency [40–42]. Table 4 summarizes localization strategies and their applicability to haircutting.

Table 4. Mapping of localization strategies between mobile robots and haircutting robots.

Category	Representative Methods	Function in Mobile Robots	Function in Haircutting
Global	Outside-in vision, Kinematic estimation, Motion capture	Absolute pose in consistent frame	Clipper-head pose for initialization
Relative	Visual odometry, IMU/encoder odometry, Force sensing	Track motion relative to local frame	Track clipper relative to moving head
Integrated Fusion	EKF, UKF, Factor graphs, Learning-based fusion	Fuse sensors for robust localization	Robust trimming under dynamic interaction

5. Hair Modeling

Hair modeling is fundamental for planning and simulation in haircutting robots. The field has evolved from physics-based approaches to learning-based reconstruction methods, each offering different trade-offs between accuracy, computational efficiency, and ease of acquisition.

Physics-based models capture hair mechanics for simulation and prediction. Mass-spring models represent hair strands as chains of particles connected by springs, capturing elasticity and gravity effects [43]. While computationally efficient, they offer limited accuracy for complex interactions. Rod-based models treat hair as elastic rods with bending and twisting stiffness, providing greater accuracy than mass-spring models but at higher computational cost for dense hair. Continuum models represent hair as a continuous medium rather than individual strands, enabling efficient computation for dense hair regions at the expense of strand-level detail.

Deep learning has enabled impressive progress in 3D hair reconstruction from images. HairNet [44] performs single-view hair reconstruction using convolutional neural networks, predicting strand geometry from monocular images. AutoHair [45] provides fully automatic hair modeling from single images, combining segmentation, orientation estimation, and strand synthesis. Neural Haircut [46] achieves prior-guided strand-based reconstruction with high-fidelity geometry from video input. Gaussian Haircut [47] reconstructs human hair with strand-aligned 3D Gaussians, enabling real-time rendering and manipulation. Table 5 compares these hair modeling approaches.

Table 5. Comparison of hair modeling approaches.

Method	Input	Output	Application
Mass-Spring [43]	Parameters	Dynamics	Simulation
HairNet [44]	Single image	3D strands	Reconstruction
AutoHair [45]	Single image	Full model	Modeling
Neural Haircut [46]	Video	Strands	High-fidelity
Gaussian [47]	Multi-view	3D Gaussians	Real-time

6. Toolpath Planning and Coverage

In autonomous haircutting, determining how the clipper should traverse the scalp constitutes a core challenge. From the mobile robotics perspective, this problem can be framed as Coverage Path Planning (CPP). CPP aims to compute trajectories ensuring complete and efficient coverage of a target area. Unlike traditional 2D coverage tasks, haircutting introduces several distinctive complexities.

Multi-pass trimming represents a fundamental requirement. Due to limited cutting depth per pass, the desired hair volume cannot be achieved through single-pass motion. The system must perform sequences of overlapping passes, each precisely aligned and depth-regulated. Shaped outcome requirements further distinguish haircutting from generic area coverage. Unlike tasks where all regions are visited equally, haircutting demands conformity to predefined 3D target shapes meeting aesthetic specifications. Safety constraints require the robot to avoid contact with sensitive anatomical regions including ears, eyes, and face, necessitating explicit integration of spatial exclusion zones into the planning framework.

It is essential to clarify the relationship between Coverage Path Planning (CPP) from mobile robotics and Computer-Aided Manufacturing (CAM) toolpath generation from CNC machining, as both paradigms contribute complementary capabilities to haircutting automation. CPP methods from mobile robotics, including boustrophedon decomposition, grid-based approaches, and graph traversal algorithms, excel at high-level workspace decomposition and systematic area coverage. These techniques partition the scalp surface into manageable regions (e.g., crown, temporal, parietal, occipital zones) and determine efficient visiting sequences that minimize redundant motion while ensuring complete coverage. In contrast, CAM algorithms from CNC machining, including contour-parallel paths, spiral toolpaths, and multi-pass finishing strategies, specialize in generating precise, surface-following trajectories with controlled tool orientation and depth. These methods optimize local cutting quality, manage material removal rates, and maintain consistent surface finish. In our proposed framework, we employ a hierarchical integration: CPP methods provide global workspace decomposition and region sequencing at the strategic level, while CAM algorithms generate detailed, geometry-conforming toolpaths within each region at the tactical level. This two-level approach combines the systematic coverage guarantees of mobile robotics with the precision surface machining capabilities of CNC systems, yielding a comprehensive planning framework optimized for both efficiency and quality in robotic haircutting.

Table 6 summarizes representative coverage planning strategies and their applicability to haircutting. Pattern-based approaches such as boustrophedon [48] and spiral patterns [49] provide systematic sweeping motions suitable for scalp partitioning into local patches. Decomposition methods including boustrophedon decomposition [10] and grid/quadtree approaches [50] enable workspace partitioning into cells for segmentation of the scalp surface. Graph-based methods such as the Chinese Postman problem [51] and minimum spanning tree approaches [11] optimize traversal with minimum cost for scalp-wide coverage. Sampling-based approaches including PRM [52] and RRT [53] establish feasible connections in configuration space for constrained regions with complex geometry. Multi-objective methods employing genetic algorithms [54], particle swarm optimization [55], and neural dynamics [56] balance trade-offs among efficiency, safety, and aesthetics. Related evolutionary approaches for robot path planning have been explored in [57,58].

Table 6. Coverage planning strategies for haircutting robots.

Category	Representative Methods	Key Characteristics	Applicability to Haircutting
Pattern-based	Boustrophedon [48], Spiral [49]	Systematic sweeping motions	Scalp partitioning into local patches
Decomposition	Boustrophedon decomposition [10], Grid/quadtree [50]	Workspace partitioning into cells	Segmentation of scalp surface
Graph-based	Chinese Postman [51], MST [11]	Traversal with minimum cost	Scalp-wide coverage optimization
Sampling-based	PRM [52], RRT [53]	Feasible connections in C-space	Constrained regions with complex geometry
Multi-objective	GA [54], PSO [55], Neural dynamics [56]	Trade-offs among multiple criteria	Balance efficiency, safety, aesthetics

We adapt Computer-Aided Manufacturing algorithms from the CNC domain to hair cutting. Given a target hairstyle specification defining length distribution and shape, the system generates optimized cutting trajectories covering the head surface, as illustrated in Figure 3. Contour-parallel paths follow head curvature analogous to surface finishing passes in CNC machining, providing uniform coverage while maintaining consistent tool orientation relative to the scalp surface. Spiral patterns provide uniform coverage through outward or inward radial sweeping, particularly suitable for crown regions. Region-based segmentation partitions the scalp into manageable sub-regions including temporal, parietal, occipital, and crown areas for prioritized processing.

Figure 3. Toolpath planning over a 3D head model showing contour-parallel trajectories, tool orientation vectors, and a zoomed inset highlighting local path detail for controlled surface-following hair-cutting motion.

An often-overlooked but critical prerequisite for precision cutting is proper hair preparation through combing, sectioning, and potentially wetting. Professional hairstylists universally employ systematic combing to detangle hair, establish consistent strand orientation, and present hair uniformly to cutting tools. Sectioning divides the scalp into manageable zones (typically 5–7 major sections) using clips or combs, enabling controlled sequential processing and preventing already-cut hair from interfering with subsequent operations. Wetting hair modifies its mechanical properties, increasing weight and reducing static, thereby improving controllability and cutting consistency. These preparatory steps directly impact the effectiveness of subsequent toolpath execution by ensuring hair is presented to the cutting tool in a predictable, organized manner. Future haircutting robot systems must integrate automated combing mechanisms, either as a dedicated pre-processing stage or as an interleaved operation between cutting passes. Recent work on robotic hair brushing [18] and compliant combing [21] provides technical foundations for such capabilities. Incorporating these preparatory operations into the overall workflow represents a critical step toward achieving professional-quality results comparable to human hairstylists.

Professional hairstylists use iterative refinement with rough cutting followed by detail passes. We implement analogous multi-pass strategies where coarse trimming provides initial bulk removal with aggressive parameters (high feed rates, coarse tolerances) to approximate the rough silhouette. Intermediate blending establishes gradients and transitions between regions. Fine finishing achieves precise target lengths with fine tolerances for aesthetic quality. Algorithm 1 presents the multi-pass toolpath generation procedure.

Algorithm Parameter Definitions. Before presenting the multi-pass toolpath generation algorithm, we clarify the representation of key parameters:

- Hair volume S_0 and residual volume S: Represented as a 3D scalar field over the head surface mesh, where each vertex stores the current hair length (in millimeters). This discretized representation enables efficient set operations through element-wise comparisons and updates.
- Target hairstyle T: Encoded as a target length field over the same mesh, specifying the desired hair length at each vertex. The notation $T^{+\epsilon}$ denotes the target with a tolerance margin ϵ (typically 1–2mm), allowing the algorithm to terminate when the residual volume is within acceptable bounds.
- Safety zones O: Defined as 3D bounding volumes (axis-aligned boxes or convex hulls) representing exclusion regions around sensitive anatomy (ears, eyes, face). Collision checking verifies that generated toolpaths maintain minimum clearance from these volumes.
- Set operations: The subtraction $S \setminus T$ computes the excess hair volume by element-wise comparison, identifying vertices where current length exceeds target length. The executed removal E_i represents the actual material removed during pass i, updating the length field based on clipper guard height and trajectory coverage.

Algorithm 1 Multi-Pass Toolpath Generation

Require: Initial hair volume S_0, Target hairstyle T, Safety zones O
Ensure: Sequence of toolpaths $\{g_i(t)\}_{i=1}^N$

```
Initialize residual volume S ← S_0
i ← 0
while S ⊈ T^{+ε} do
    i ← i + 1
    Compute removal target R_i ← S \ T
    Generate collision-free toolpath g_i(t) covering R_i
    Verify g_i(t) ∩ O = ∅ for all t
    Execute pass and update S ← S \ E_i
end while
return {g_i(t)}_{i=1}^N
```

7. Control and Execution

The final component of autonomous haircutting lies in execution, where planned trajectories must be realized safely, efficiently, and with desired trimming quality. Achieving CNC-level precision requires sophisticated motion control approaches that address the unique challenges of operating in close proximity to a human subject.

High-bandwidth servo control on each axis employs closed-loop control with position feedback at 1–10 kHz rates. Feedforward compensation based on inverse dynamics models minimizes trajectory tracking errors, achieving positioning accuracy below 0.5 mm. Coordinated multi-axis motion synchronizes all five axes through real-time interpolation generating setpoints while maintaining geometric path accuracy [59]. Adaptive feed rates adjust cutting speed based on hair properties through force feedback, where increasing resistance triggers deceleration to prevent tool jamming.

Humans naturally move during extended procedures, presenting a significant challenge for maintaining cutting accuracy. Vision systems track head pose at 100 Hz, detecting movements within 10 ms. Predictive algorithms anticipate motion trends, enabling proactive trajectory adaptation rather than reactive correction. Minor movements trigger local trajectory warping, while large movements pause operations, replan globally, and resume safely. This hybrid approach combining active compensation and passive stabilization through padded head rests maximizes effectiveness.

Close human-robot proximity demands multiple safety layers [4]. Table 7 summarizes the key safety mechanisms employed in haircutting robots. Variable impedance control adjusts apparent stiffness based on task phase and collision risk [60]. During normal cutting, high stiffness maintains precision; upon detecting unexpected resistance, stiffness reduces immediately, allowing safe deflection.

Table 7. Safety mechanisms in haircutting robots.

Mechanism	Function
Impedance control [60]	Variable stiffness based on task phase
Collision avoidance [61]	Multi-layer prevention and reaction
Force limiting	Hardware-enforced maximum forces
Emergency stop	Immediate tool retraction
Compliant actuators	Passive safety via SEA/VSA

Multi-layer collision avoidance ensures safety through planning-stage collision checking that verifies trajectory safety before execution, proximity-based intervention that triggers evasive actions when sensors detect dangerous approach, and contact-based reaction that immediately stops motion upon unexpected contact [61]. Hardware safety mechanisms include torque-limited motors that physically constrain maximum forces, mechanical stops preventing excessive tool excursions, and spring-loaded retraction mechanisms that engage during power failures.

Table 8 summarizes representative actuators and their roles in haircutting robots. Motion actuation employs DC/BLDC motors, servo motors, stepper motors, and linear actuators for driving arm joints, end-effector orientation, and positioning. End-effector actuators include vibration motors for clippers, rotary servos for scissors, and micro linear actuators for guard adjustment. Compliant actuators such as SEA, VSA, and MR clutches/dampers enable safe contact, force control, and compliance tuning. Auxiliary systems encompass tool changers, vacuum motors for hair collection, and blower actuators for airflow assistance.

Table 8. Actuator categories and their roles in haircutting robots.

Category	Representative Actuators	Key Role
Motion actuation	DC/BLDC motors, Servo motors, Stepper motors, Linear actuators	Driving arm joints, end-effector orientation, positioning
End-effector	Vibration motors (clipper), Rotary servo (scissors), Micro linear (guard)	Trimming execution, cutting length adjustment
Compliant	SEA, VSA, MR clutches/dampers	Safe contact, force control, compliance tuning
Auxiliary	Tool changer, Vacuum motors, Blower actuators	Tool switching, hair collection, airflow assistance
HRI	Haptic feedback, Audio output	User alerts, touch cues, voice interaction

8. Open Challenges and Future Directions

Hair exhibits enormous diversity across individuals and ethnicities. Thickness varies 10-fold, curvature ranges from straight to tightly coiled, and density varies 3-fold [7]. Developing inclusive models representing all hair types is both a technical necessity and an ethical imperative for ensuring equitable access to robotic haircutting services. Achieving truly inclusive haircutting automation requires comprehensive datasets encompassing the full spectrum of human hair diversity, including Type 1 (straight) through Type 4 (coily) hair across different ethnicities. Current hair modeling and cutting research has disproportionately focused on straight to wavy hair types common in East Asian and European populations, with limited attention to the kinky and coiled textures predominant in African and Afro-Caribbean populations. These hair types exhibit fundamentally different mechanical properties, including higher tensile strength, lower elasticity, and greater tangling propensity. These characteristics demand adapted cutting strategies, specialized tools, and modified force control parameters. Developing equitable robotic haircutting systems requires investment in diverse training data collection, development of hair-type-specific models, and validation across representative user populations to ensure that automation benefits are accessible to all communities, not merely those whose hair characteristics align with existing research biases.

Long-horizon autonomy presents another significant challenge, as complete hairstyling sessions span 30–60 min involving thousands of individual cuts. Maintaining consistent precision while adapting to changing conditions requires robust long-horizon planning that can recover from errors and adapt to unexpected situations. Consider a practical example: cutting a medium-length hairstyle with 100,000 strands to achieve uniform 5 cm length. Assuming 10mm cutting width per pass and 50% overlap for quality, approximately 2000 individual cutting strokes are required. At a conservative 2-s cycle time per stroke (approach, cut, retract), the total operation time exceeds 60 min. During this extended period, cumulative positioning errors, tool wear, hair property changes due to drying, and inevitable human movements all degrade cutting quality. Robust long-horizon autonomy requires continuous quality monitoring through vision feedback, adaptive recalibration based on landmark tracking, periodic error correction passes, and graceful degradation strategies when performance drifts beyond acceptable bounds. These capabilities extend significantly beyond current demonstration-level prototypes that operate for only a few minutes under constrained conditions.

Aesthetic evaluation remains poorly quantified, with no standardized metrics for hairstyle quality. Developing benchmarks incorporating both geometric accuracy and aesthetic assessment is essential for objective comparison of different systems and approaches. Unlike manufacturing operations where quality can be measured through geometric tolerances and surface finish metrics, hairstyle quality encompasses subjective aesthetic dimensions. These dimensions include facial symmetry enhancement, style coherence, transition smoothness between regions, and alignment with contemporary fashion norms. Professional hairstylists evaluate quality through holistic visual inspection considering proportions relative to facial features, balance between left and right sides, smooth gradients in fade regions, and overall stylistic harmony. Translating these qualitative assessments into quantifiable metrics suitable for robotic optimization represents a fundamental research challenge. Potential approaches include perceptual loss functions trained on human preference data, multi-view geometric analysis comparing target and achieved styles, and automated detection of common defects such as uneven lengths, harsh transitions, or asymmetry. However, developing truly comprehensive evaluation frameworks that capture the full complexity of aesthetic judgment remains an open problem requiring interdisciplinary collaboration between computer vision, psychology, and professional hairstyling communities.

Sim-to-real transfer poses ongoing challenges. Physics-based hair simulation combined with photorealistic rendering enables algorithm development in simulation, but bridging the gap to real-world deployment requires careful domain adaptation. Current physics simulators can model individual hair strand dynamics with reasonable accuracy. However, scaling to realistic full-head simulations with 100,000+ strands remains computationally prohibitive for real-time application. Simplified models using strand clustering or continuum approximations achieve computational tractability but introduce sim-to-real gaps in cutting dynamics, particularly for curly and textured hair where individual strand interactions dominate bulk behavior. Rendering realistic hair appearance for perception algorithm training faces additional challenges. Subsurface scattering, anisotropic reflection, and fine geometric detail require expensive ray-tracing techniques. Practical sim-to-real transfer for haircutting likely requires hybrid approaches combining coarse physics simulation for motion planning, learned corrections from real-world data for dynamics prediction, and domain randomization techniques to improve robustness. Recent advances in differentiable physics simulation and neural rendering offer promising directions but have not yet been validated for hair manipulation tasks at the scale and fidelity required for autonomous haircutting.

Learning-based approaches offer promising directions for advancing haircutting robot capabilities. Behavior cloning [62] and demonstration-based models [63] can capture stylistic features of professional barbers for robotic execution. Imitation learning provides a powerful paradigm for transferring human expertise to robots [64,65]. Reinforcement learning enables policy optimization through trial-and-error [66–68], adapting trimming trajectories to user preferences and dynamic hair properties. Recent vision-language-action frameworks [69–71] unify perception and language to produce action commands, enabling natural language hairstyle specification that could make robotic haircutting more accessible to users.

Integration with autonomous systems provides additional sources of technology transfer. Deep neural networks for perception [72,73], control barrier functions for safety [74], and model predictive control [75] from autonomous driving [76,77] provide templates for haircutting systems. Methods for covering complex 3D surfaces, segmenting irregular workspaces, and executing visual servoing from UAV coverage applications [78,79] are directly pertinent to scalp coverage. Graph neural networks for multi-robot coordination [80] and Pareto-optimal motion planning [81] offer additional algorithmic foundations.

Economic and social considerations merit careful attention. Detailed cost-benefit analysis must assess system costs, throughput improvements, and customer willingness to pay. Identifying viable market segments including budget salons, assisted living facilities, and military applications guides commercialization strategy. Understanding effects on hairstylist employment and developing augmentation rather than replacement approaches addresses social concerns while preserving human expertise. Robotic assistance could make professional hairstyling accessible to individuals with disabilities or limited mobility, expanding the reach of quality personal care services. A roadmap for practical deployment has been outlined in [3].

9. Conclusions

This survey has provided a comprehensive review of robotic haircutting through the lens of CNC machining principles, proposing a unified framework treating hair manipulation with industrial manufacturing rigor. We systematically analyzed the field across system architectures, sensing modalities, hair modeling techniques, toolpath planning strategies, and control approaches.

The CNC-inspired paradigm offers several key insights. Framing haircutting as coverage path planning enables systematic algorithm development drawing on decades of mobile robotics research. Multi-pass toolpath strategies from CNC machining directly apply to iterative hair removal with progressive refinement. Multimodal sensing fusion addresses the localization challenge in dynamic human-robot interaction where the workspace itself is in motion. Safety-critical control from surgical and collaborative robotics ensures safe operation in close proximity to sensitive anatomy.

Key technical challenges remain, including hair property variability across diverse populations, long-horizon autonomy for complete styling sessions, aesthetic evaluation metrics for quality assessment, and sim-to-real transfer for practical deployment. Future progress will likely depend on hybrid frameworks combining model-based control with learning-driven adaptation, integration of vision-language-action models for natural interaction, and comprehensive real-world validation across diverse user populations.

By bridging service robotics and precision manufacturing, this survey provides researchers with a structured foundation for advancing haircutting robot technology toward practical deployment. The systematic approach to precision, safety, and quality control addresses key barriers that have prevented deployment for decades. Building on industrial automation's solid foundation, we can finally bring the benefits of robotic precision to personal care services.

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Use of AI and AI-Assisted Technologies

During the preparation of this work, the author(s) used ChatGPT/Claude for rephrasing and grammatical corrections and the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

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