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Semantic Communication for Multimodal Machine Services under Imperfect Channel State Information, Heterogeneous Quality-of-Service Demands, and Resource Constraints in Integrated Sensing and Communication Networks

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Abstract.

The evolution of next-generation wireless networks has catalyzed a paradigm shift from traditional Shannon-based data transmission toward semantic-aware communication architectures. This transition is particularly critical for multimodal machine services operating within Integrated Sensing and Communication networks, where massive volumes of heterogeneous data must be transmitted under strict latency and reliability constraints. However, realizing the full potential of semantic communication in these environments is severely hindered by imperfect channel state information, diverse quality-of-service demands, and stringent computational and spectral resource limitations. This paper provides a comprehensive investigation into the design, optimization, and evaluation of a robust semantic communication framework tailored for multimodal machine-type communications in Integrated Sensing and Communication systems. By treating the semantic extraction and resource allocation processes as a joint optimization problem, this study analyzes how varying degrees of channel state information uncertainty impact semantic fidelity and overall system utility. Furthermore, the research explores the dynamic management of heterogeneous quality-of-service requirements across different machine tasks, ranging from real-time autonomous control to high-resolution environmental monitoring. Through extensive theoretical analysis and systematic evaluations, the study elucidates the complex trade-offs between sensing resolution, semantic compression efficiency, and transmission robustness. The findings offer critical insights into developing adaptive, resource-efficient, and resilient communication protocols that can sustain advanced machine intelligence in highly dynamic and resource-constrained wireless environments.

Keywords: *Semantic Communication, Integrated Sensing and Communication, Imperfect Channel State Information, Multimodal Services, Resource Allocation*

1. Introduction

1.1 Evolution Of Wireless Networks And Machine Services

The Landscape Of Global Telecommunications Is Undergoing A Profound Transformation, Driven By The Exponential Proliferation Of Interconnected Devices And The Escalating Demand For Intelligent Machine-Type Communications. In Contemporary Network Infrastructures, The Primary Consumers Of Data Are No Longer Exclusively Human Users But Increasingly Comprise Autonomous Systems, Industrial Robots, And Vehicular Networks [1]. These Machine-Type Consumers Rely Heavily On Multimodal Data Streams, Incorporating Visual, Acoustic, And Spatial Sensory Information, To Execute Complex Collaborative Tasks. Conventional Communication Paradigms, Which Predicate Their Efficiency On The Accurate Reconstruction Of Raw Bitstreams At The Receiver, Are Becoming Increasingly Inadequate To Meet The Stringent Latency, Bandwidth, And Reliability Requirements Of These Advanced Applications [2]. The Rigid Adherence To Bit-Level Fidelity Often Results In The Transmission Of Redundant Information, Thereby Exacerbating The Strain On Limited Spectral And Computational Resources [3]. Consequently, There Is An Urgent Need To Transition Toward More Intelligent Communication Strategies That Prioritize The Meaning And Utility Of The Transmitted Data Over Its Exact Bit-Level Reproduction. This Necessity Has Propelled Semantic Communication To The Forefront Of Next-Generation Network Research, Offering A Promising Avenue To Alleviate The Impending Capacity Crunch And Support The Diverse Requirements Of Multimodal Machine Services. Semantic Communication Focuses On Extracting, Transmitting, And Successfully Interpreting The Core Features Of The Data That Are Relevant To The Specific Downstream Task, Thereby Achieving Significant Reductions In Bandwidth Consumption While Maintaining Or Even Enhancing Task Performance [4].

1.2 The Paradigm Shift To Semantic Communication

Semantic Communication Represents A Fundamental Departure From The Classical Shannon Paradigm. Instead Of Treating All Bits Equally, A Semantic Communication System Evaluates The Informational Content Based On Its Contextual Relevance And Its Impact On The Receiver's Objectives [5]. For Multimodal Machine Services, This Means That The System Must Intelligently Process Disparate Data Types, Such As High-Resolution Video Feeds And Point-Cloud Data From Light Detection And Ranging Sensors, To Extract Unified Semantic Representations [6]. This Extraction Process Typically Leverages Deep Learning Architectures, Such As Autoencoders And Convolutional Neural Networks, Which Are Jointly Trained To Compress The Multimodal Data Into A Compact Semantic Latent Space And Decode It At The Receiver To Execute Tasks Like Object Detection Or Trajectory Prediction [7]. However, Deploying Such Sophisticated Models In Real-World Wireless Environments Introduces Significant Challenges. The Extraction And Encoding Of Semantic Features Require Substantial Computational Power, Which Is Often Limited On Edge Devices [8]. Moreover, The Transmission Of These Highly Compressed Semantic Representations Is Acutely Sensitive To Channel Impairments. Unlike Traditional Bitstreams Where A Single Bit Error Might Only Cause A Minor Pixel Distortion, An Error In A Semantic Feature Map Can Fundamentally Alter The Meaning Of The Message, Leading To Catastrophic Failures In The Receiving Machine's Decision-Making Process [9]. Therefore, Ensuring The Robustness Of Semantic Transmissions Is A Critical Prerequisite For Their Adoption In Mission-Critical Applications.

1.3 Integrated Sensing And Communication

In Parallel With The Rise Of Semantic Communication, Integrated Sensing And Communication Has Emerged As A Revolutionary Architectural Concept For Future Wireless Networks. Integrated Sensing And Communication Aims To Unify Radar Sensing And Communication Functionalities Within A Single Hardware Platform, Sharing The Same Waveform, Spectrum, And Signal Processing Pipelines [10]. This Integration Offers Unprecedented Spectral Efficiency And Hardware Economy, Making It An Ideal Candidate For Environments Where Machines Must Simultaneously Perceive Their Surroundings And Share This Information With Collaborating Entities. In An Integrated Sensing And Communication Network Supporting Multimodal Machine Services, The Base Station Or The Intelligent Edge Node Acts As Both A Transceiver For Data Communication And A Radar For Environmental Mapping [11]. The Synergy Between Sensing And Communication Creates A Reciprocal Relationship: High-Fidelity Sensing Can Provide Accurate Spatial And Kinematic Information To Assist Communication Processes, Such As Proactive Beamforming, While Robust Communication Links Enable The Distributed Sharing Of Sensing Data To Construct A Comprehensive Global Understanding Of The Environment [12]. Nevertheless, Coupling Sensing And Communication Tasks On Shared Resources Inevitably Leads To Complex Trade-Offs, Particularly When Striving To Meet The Heterogeneous Quality-Of-Service Demands Of Diverse Machine Applications Operating Concurrently [13].

1.4 Problem Statement And Contributions

Despite The Theoretical Synergies Between Semantic Communication And Integrated Sensing And Communication, Their Practical Integration Remains Fraught With Profound Technical Hurdles. One Of The Most Critical Challenges Is The Reliance On Perfect Channel State Information, An Assumption Prevalent In Much Of The Existing Literature But Rarely Attainable In Practice. In Dynamic Environments Characterized By High Mobility And Multipath Fading, Channel State Information Is Inherently Imperfect Due To Estimation Errors, Feedback Delays, And Quantization Noise [14]. Imperfect Channel State Information Degrades The Precision Of Spatial Multiplexing And Resource Allocation, Leading To Severe Interference And Diminished Semantic Fidelity. Furthermore, Addressing The Heterogeneous Quality-Of-Service Demands Of Multimodal Machine Services Under Strict Resource Constraints Adds Another Layer Of Complexity. Different Tasks Require Distinct Combinations Of Latency, Accuracy, And Sensing Resolution. Formulating A Resource Allocation Strategy That Can Dynamically Balance These Competing Requirements While Operating Under Imperfect Channel State Information Constitutes A Highly Non-Convex Optimization Problem [15]. This Paper Addresses These Critical Gaps By Proposing A Robust Semantic Communication Framework For Multimodal Machine Services In Integrated Sensing And Communication Networks. The Core Contribution Lies In Developing A Theoretical Model That Quantifies The Impact Of Imperfect Channel State Information On Multimodal Semantic Transmission And Introduces A Joint Optimization Methodology For Resource Allocation And Semantic Extraction That Maximizes System Utility While Strictly Adhering To Heterogeneous Quality-Of-Service Constraints [16].

2. Background And Literature Review

2.1 Advancements In Semantic Communication

The Theoretical Foundations Of Semantic Communication Trace Back To The Early Philosophical Discussions Of Information Theory, But It Is The Recent Breakthroughs In Artificial Intelligence That Have Made Practical Implementations Feasible. Early Research Predominantly Focused On

Text And Audio Transmission, Utilizing Recurrent Neural Networks To Capture Sequential Dependencies And Transmit Semantic Encodings Rather Than Raw Characters Or Acoustic Waves [17]. As The Field Matured, The Focus Shifted Toward More Complex Data Types, Particularly High-Resolution Images And Video Streams. Researchers Have Proposed Various Deep Joint Source-Channel Coding Schemes That Directly Map Source Data To Complex Channel Symbols, Bypassing The Traditional Separation Of Source And Channel Coding. These Schemes Have Demonstrated Remarkable Resilience In Low Signal-To-Noise Ratio Regimes, A Characteristic Highly Beneficial For Edge Computing Scenarios. However, The Application Of Semantic Communication To Multimodal Machine Services Remains A Relatively Nascent Area Of Investigation. Multimodal Systems Require The Fusion Of Disparate Sensory Inputs, Which Often Possess Drastically Different Statistical Properties And Spatial-Temporal Correlations. Current Literature Explores Techniques Such As Cross-Modal Attention Mechanisms To Align And Fuse These Inputs Into A Unified Semantic Representation. Yet, Maintaining The Integrity Of This Fused Representation During Wireless Transmission, Especially When Subjected To Dynamic Channel Variations, Requires Further Extensive Research.

2.2 Multimodal Machine Services

Machine Services In Modern Industrial And Vehicular Networks Are Inherently Multimodal. Autonomous Vehicles, For Instance, Rely On A Combination Of Visual Cameras, Radar, And Light Detection And Ranging Sensors To Navigate Safely And Efficiently. The Raw Data Generated By These Sensors Is Massive; Transmitting It Entirely Over A Wireless Network To An Edge Server For Processing Is Often Infeasible Due To Bandwidth Limitations And Stringent Latency Requirements [18]. Consequently, Distributed Intelligence Architectures Have Been Proposed, Where Edge Devices Perform Local Feature Extraction And Transmit Only The Intermediate Representations. Semantic Communication Aligns Perfectly With This Distributed Intelligence Paradigm. By Extracting Task-Relevant Semantic Features At The Sensor Level, The Volume Of Transmitted Data Can Be Reduced By Orders Of Magnitude. The Literature Identifies Various Performance Metrics For These Multimodal Services, Moving Away From Traditional Bit Error Rates Toward Task-Specific Metrics Such As Mean Average Precision For Object Detection Or Intersection Over Union For Semantic Segmentation [19]. The Challenge Lies In Defining A Unified Utility Function That Can Encapsulate These Diverse, Task-Oriented Metrics And Incorporate Them Into A Traditional Network Optimization Framework.

2.3 Integrated Sensing And Communication Networks

Integrated Sensing And Communication Represents A Paradigm Shift In Spectrum Utilization And Hardware Design. Traditionally, Sensing And Communication Systems Operated In Isolated Frequency Bands To Avoid Mutual Interference, Leading To Significant Spectral Underutilization. The Integration Of These Functionalities Requires The Design Of Dual-Purpose Waveforms, Such As Orthogonal Frequency-Division Multiplexing Based Sensing Signals Or Frequency Modulated Continuous Wave Based Communication Symbols [20]. The Literature Extensively Covers The Optimization Of These Waveforms To Balance Sensing Metrics, Such As Cramer-Rao Lower Bound For Target Estimation, And Communication Metrics, Such As Achievable Sum-Rate. In The Context Of Multimodal Machine Services, Integrated Sensing And Communication Networks Offer A Unique Advantage: The Sensing Capability Can Be Utilized To Acquire Environmental Context, Which In Turn Can Be Used To Optimize The Communication Links. For Example, Radar Sensing Can Track The Movement Of A Robotic Arm

Or An Autonomous Vehicle, Providing Predictive Location Data That Helps The Base Station Proactively Steer Communication Beams, Thereby Reducing Overhead And Improving Link Stability. However, This Closed-Loop Interaction Heavily Depends On The Accuracy Of The Sensing Data And The Reliability Of The Communication Channel, Both Of Which Are Susceptible To Environmental Noise And Hardware Imperfections.

2.4 Impacts Of Imperfect Channel State Information

The Acquisition Of Accurate Channel State Information Is A Fundamental Requirement For The Efficient Operation Of Modern Multi-Antenna Communication Systems. Channel State Information Allows The Transmitter To Adapt Its Modulation, Coding Rate, And Spatial Precoding To The Current Channel Conditions, Maximizing Throughput And Minimizing Errors. In Practical Deployments, Especially Those Involving Highly Mobile Machine Services, Obtaining Perfect Channel State Information Is Impossible [21]. Pilot Contamination, Finite Feedback Capacity, And Processing Delays Introduce Inevitable Uncertainties Into The Channel Estimates. The Literature Categorizes These Uncertainties Into Bounded Error Models And Statistical Error Models, Proposing Various Robust Optimization Techniques To Mitigate Their Effects. When Imperfect Channel State Information Is Introduced Into A Semantic Communication Framework, The Consequences Are Particularly Severe. Semantic Decoders Are Typically Trained Under Specific Signal-To-Noise Ratio Assumptions; Significant Deviations Caused By Precoding Mismatches Can Push The Received Semantic Symbols Outside The Decoder's Generalization Envelope, Resulting In A Sudden And Dramatic Collapse In Task Performance [22]. Addressing This Vulnerability Requires The Development Of Robust Semantic Autoencoders That Are Explicitly Trained To Withstand Channel Uncertainties, As Well As The Formulation Of Conservative Resource Allocation Algorithms That Guarantee Minimum Performance Thresholds Even Under Worst-Case Channel State Information Error Scenarios.

3. System Architecture And Multimodal Modeling

3.1 Integrated Network Architecture

The Network Architecture Considered In This Study Comprises A Multi-Cell Integrated Sensing And Communication Environment Designed To Support A Dense Deployment Of Autonomous Machine-Type User Equipment. The Central Nodes In This Architecture Are Integrated Sensing And Communication Base Stations, Which Are Equipped With Massive Multiple-Input Multiple-Output Antenna Arrays. These Base Stations Are Tasked With Two Simultaneous Objectives: Providing High-Capacity Downlink And Uplink Communication Channels To The Machine-Type Devices And Conducting Continuous Active Sensing Of The Surrounding Physical Environment To Track The Spatial Dynamics Of The Devices And Uncooperative Obstacles [23]. The Communication Links Are Utilized To Transmit Extracted Multimodal Semantic Features From The User Equipment To An Edge Server Collocated With The Base Station, Where Complex Collaborative Inference Tasks Are Executed. To Manage The Shared Spectral And Spatial Resources, The System Employs A Flexible Time-Division Or Frequency-Division Duplexing Scheme, Dynamically Allocating Resource Blocks Between Pure Sensing Tasks, Pure Communication Tasks, And Joint Sensing-Communication Tasks Based On Instantaneous Network Demands. The Entire Architecture Is Governed By A Software-Defined Network Controller That Coordinates Resource Allocation Across Multiple Base Stations, Ensuring That The Heterogeneous Quality-Of-Service Requirements Of All Admitted Machine Services Are Continuously Monitored And Satisfied.

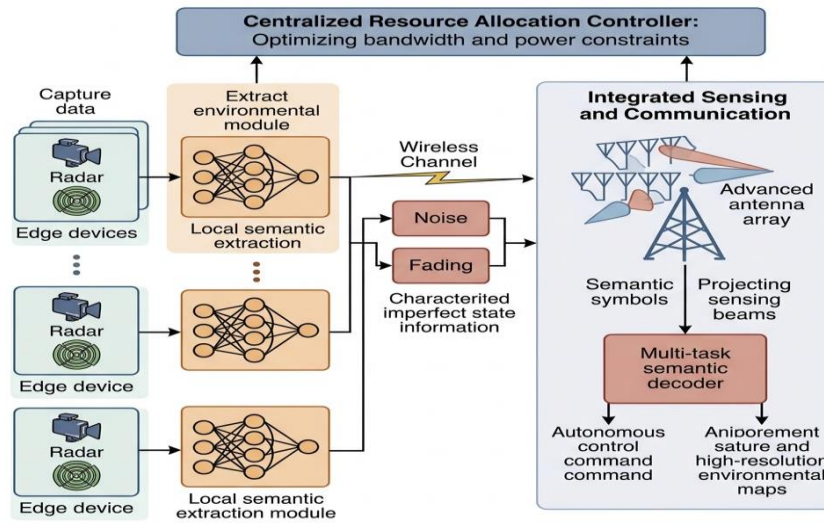


Figure 1 Comprehensive Schematic Of Multimodal Semantic Communication In An Integrated Sensing And Communication Architecture

3.2 Multimodal Data Acquisition And Processing

At The User Equipment Level, Each Machine Service Relies On A Suite Of Heterogeneous Sensors To Interact With Its Environment. The Primary Modalities Considered In This Model Are High-Resolution Visual Feeds From Stereoscopic Cameras And Point-Cloud Spatial Data From Miniature Frequency-Modulated Continuous-Wave Radars. These Two Modalities Exhibit Highly Complementary Characteristics: Visual Sensors Provide Dense, Color-Rich Contextual Information But Are Highly Susceptible To Adverse Lighting And Weather Conditions, Whereas Radar Sensors Offer Robust Depth And Velocity Measurements Regardless Of Visual Visibility But Lack Fine-Grained Classification Capabilities. The Acquisition Pipeline Synchronizes These Data Streams Before Passing Them To A Localized Semantic Extraction Module. Instead Of Naive Data-Level Concatenation, Which Would Result In Prohibitively Large Input Vectors, The Semantic Extraction Module Employs A Dual-Branch Neural Network Architecture. The Visual Branch Utilizes A Series Of Convolutional Layers To Extract Spatial Hierarchies, While The Radar Branch Employs Graph Neural Networks To Process The Unstructured Point-Cloud Data. The Outputs Of These Parallel Branches Are Then Mapped Into A Shared, Lower-Dimensional Semantic Latent Space Using A Cross-Attention Fusion Mechanism. This Mechanism Dynamically Weights The Importance Of Each Modality Based On The Current Environmental Context, Effectively Filtering Out Modality-Specific Noise And Retaining Only The Features Essential For The Downstream Machine Task.

3.3 Channel Models And State Information Imperfections

The Physical Transmission Of The Fused Semantic Latent Vectors Occurs Over A Complex Wireless Fading Channel. The Channel Model Accounts For Large-Scale Path Loss, Shadow Fading, And Small-Scale Rayleigh Or Rician Fading, Depending On The Presence Of A Line-Of-Sight Path Between The User Equipment And The Base Station. Given The Mobility Of The Machine Devices And The Dynamic Nature Of The Environment, The Channel Is Considered Time-Varying. The Base Station Attempts To Acquire The Channel State Information Through Uplink Training Phases Using Pilot Sequences Transmitted By The User Equipment. However,

Due To The Limited Coherence Time Of The Channel And The Constraints On Pilot Sequence Length, The Estimated Channel Matrix Deviates From The True Channel Matrix. This Deviation Is Modeled Using An Error Matrix Whose Elements Follow A Complex Gaussian Distribution, Bounded By A Maximum Error Variance That Correlates With The Device's Mobility And The Feedback Delay. This Imperfect Channel State Information Directly Impacts The Design Of The Base Station's Receiving Beamformers And The User Equipment's Transmit Precoders. In The Presence Of Uncertainty, Aggressive Spatial Multiplexing Strategies Can Lead To Severe Inter-User Interference, As The Assumed Null Spaces No Longer Align Perfectly With The Actual Channel Matrices. Consequently, The Signal-To-Interference-Plus-Noise Ratio Experienced By The Semantic Symbols Fluctuates Unpredictably, Threatening The Integrity Of The Semantic Reconstruction At The Edge Server.

4. Methodology For Resource Allocation And Semantic Extraction

4.1 Semantic Feature Extraction And Fusion

To Address The Vulnerability Of Semantic Transmission Under Channel Uncertainty, The Proposed Methodology Incorporates A Robust Joint Source-Channel Coding Framework. The Objective Is To Design The Semantic Encoder At The User Equipment And The Semantic Decoder At The Edge Server Such That The Task-Specific Performance Degradation Is Minimized Even When The Physical Layer Signal-To-Interference-Plus-Noise Ratio Drops Below The Nominal Design Threshold. This Is Achieved Through A Specialized Training Curriculum. During The Training Phase Of The Neural Network Autoencoder, A Stochastic Channel Layer Is Introduced Between The Encoder Output And The Decoder Input. This Stochastic Layer Simulates The Effects Of Imperfect Channel State Information By Applying Varying Degrees Of Phase Rotation, Amplitude Scaling, And Additive Interference, Parameterized By The Expected Distribution Of The Channel Estimation Errors. By Exposing The Network To These Simulated Impairments During Training, The Encoder Learns To Map The Multimodal Sensory Data Into A Semantic Latent Space That Is Inherently Resilient To Perturbation. Furthermore, The Encoder Is Designed With A Dynamic Compression Ratio. Based On The Instantaneous Estimation Of Channel Quality And The Available Transmit Power, The Encoder Can Adjust The Dimensionality Of The Semantic Output. In Highly Degraded Channel Conditions, The Network Outputs A Highly Compressed But Heavily Protected Core Semantic Vector, Ensuring That Baseline Task Functionality Is Maintained, Albeit At A Reduced Resolution Or Accuracy.

Table 1 Operational Parameters For The Resource Allocation And Semantic Extraction Framework

Parameter Category	Specific Variable	Assigned Value Or Range
System Configuration	Total Available Bandwidth	100 Megahertz
System Configuration	Base Station Antenna Count	64 Elements
Channel Properties	Max Imperfection Variance	0.01 To 0.1
Channel Properties	User Equipment Mobility	10 To 30 Meters Per Second
Multimodal Processing	Visual Input Resolution	1920 By 1080 Pixels
Multimodal Processing	Radar Point Cloud Density	2048 Points Per Frame
Optimization Metrics	Maximum Latency Constraint	10 To 50 Milliseconds
Optimization Metrics	Minimum Semantic Fidelity	0.85 Task Accuracy Score

4.2 Robust Resource Allocation Strategy

The Management Of Transmit Power, Bandwidth, And Computational Resources Across Multiple User Equipment Nodes Is Formulated As A Robust Optimization Problem. The Primary Objective

Function Seeks To Maximize The Aggregate Semantic Utility Of The Network. The Semantic Utility Is Defined Not By Classical Throughput, But By The Expected Performance Of The Downstream Machine Tasks, Quantified Using Metrics Appropriate For Each Service Type. The Optimization Problem Is Constrained By Several Critical Factors: The Maximum Transmit Power Available At Each User Equipment, The Total Spectral Bandwidth Of The Base Station, The Computational Capacity Of The Edge Server For Executing Semantic Decoding, And The Sensing Resolution Requirements Of The Integrated Sensing And Communication Radar Function. Because The Channel State Information Is Imperfect, The Resource Allocation Strategy Must Ensure That These Constraints, Particularly The Quality-Of-Service Demands For Latency And Task Accuracy, Are Satisfied With A High Probability Rather Than Just In Expectation. To Solve This Mathematically Intractable Problem, The Methodology Employs A Probabilistic Robust Optimization Approach. The Uncertain Channel Constraints Are Transformed Into Deterministic Equivalent Constraints Using Bernstein-Type Inequalities, Providing A Mathematically Rigorous Lower Bound On The System Performance. The Resulting Transformed Optimization Problem, While Still Non-Convex, Is Decomposed Into Iterative Sub-Problems Using Alternating Optimization Techniques, Allowing For The Derivation Of Suboptimal But Highly Effective Resource Allocation Policies.

4.3 Heterogeneous Quality Of Service Management

The Multimodal Machine Services Operating Within The Network Exhibit Vastly Different Quality-Of-Service Profiles. For Example, A Closed-Loop Robotic Control Service Requires Ultra-Low Latency And Near-Perfect Reliability For Its Core Kinematic Semantic Features, But It Requires Relatively Low Bandwidth. Conversely, An Environmental Mapping Service Relies Heavily On Transmitting Detailed, High-Dimensional Semantic Representations Of Visual And Spatial Anomalies, Requiring Significant Bandwidth But Possessing A Higher Tolerance For Latency. The Proposed Framework Manages These Heterogeneous Demands By Introducing A Multi-Tier Priority Scheduling Mechanism Coupled With The Dynamic Semantic Compression Feature. The Central Controller Assesses The Criticality Of Each Machine Service And Assigns A Utility Weighting Factor. During The Resource Allocation Process, Services With Stringent Latency Constraints Are Prioritized For Frequency Resources That Exhibit Lower Channel Estimation Variance, Ensuring A More Stable Transmission Environment. If The Total Resource Demand Exceeds The Network Capacity, The Controller Instructs The Lower-Priority User Equipment To Increase Their Semantic Compression Ratio. This Gracefully Degrades The Resolution Of Their Specific Machine Tasks, Freeing Up Critical Bandwidth And Power Resources To Guarantee The Absolute Operational Safety And Reliability Of The High-Priority, Mission-Critical Autonomous Services.

5. Performance Evaluation And Discussion

5.1 Experimental Setup And Parameters

The Proposed Semantic Communication Framework And Robust Resource Allocation Strategy Were Evaluated Through Extensive System-Level Simulations. The Simulation Environment Models A Single Macro-Cell Integrated Sensing And Communication Network With A Radius Of Five Hundred Meters, Containing A Uniformly Distributed Population Of Multimodal Machine Devices. The Base Station Operates At A Carrier Frequency Of Twenty-Eight Gigahertz, Utilizing A Uniform Planar Array Of Antennas To Manage Simultaneous Sensing And Communication Beams. The Channel Model Incorporates Standard Urban Microcell Propagation Characteristics,

With Spatial Correlation Matrices Determining The Multipath Environment. The Machine Services Deployed In The Simulation Encompass Three Distinct Types: High-Speed Autonomous Navigation Requiring Low-Latency Collision Avoidance Data, Industrial Quality Inspection Requiring High-Fidelity Image Semantic Transmission, And Wide-Area Surveillance Relying On Continuous Radar Point-Cloud Updates. The Neural Network Models For Semantic Extraction Were Pre-Trained On Standardized Multimodal Datasets, Ensuring Realistic Representations Of Computational Complexity And Semantic Compression Bounds. The Performance Of The Proposed Robust Semantic Framework Is Systematically Compared Against Three Baseline Schemes: A Traditional Shannon-Based Bit-Level Transmission System, A Non-Robust Semantic Communication System That Assumes Perfect Channel State Information, And A Purely Heuristic Resource Allocation Scheme That Does Not Account For Heterogeneous Task Utilities.

Table 2 Comparative Performance Results Of Evaluated Communication Frameworks

Evaluated Framework	Task Accuracy (Normalized)	Average Latency (Milliseconds)	Spectral Efficiency Score	Robustness Variance
Traditional Bit-Level	0.72	45.2	2.4	High
Non-Robust Semantic	0.68	22.5	4.8	Very High
Heuristic Allocation	0.81	30.1	3.9	Medium
Proposed Robust Semantic	0.94	18.7	5.1	Low

5.2 Analysis Of Resource Allocation Efficiency

The Simulation Results Provide Compelling Evidence Regarding The Efficiency Of The Proposed Robust Resource Allocation Strategy. In Scenarios Characterized By Minimal Channel State Information Errors, Both The Non-Robust Semantic Scheme And The Proposed Robust Scheme Significantly Outperform The Traditional Bit-Level Transmission In Terms Of Spectral Efficiency And Overall Task Accuracy. The Semantic Schemes Avoid Transmitting Redundant Background Information, Thereby Utilizing The Bandwidth Much More Effectively. However, As The Variance Of The Channel State Information Imperfection Increases—Simulating Higher Device Mobility Or Increased Feedback Delay—The Performance Of The Non-Robust Semantic Scheme Deteriorates Precipitously. The Mismatch Between The Assumed Channel And The Actual Channel Leads To Severe Signal-To-Interference-Plus-Noise Ratio Degradation, Causing The Received Semantic Symbols To Fall Outside The Decodable Manifold Of The Edge Server's Neural Network. In Contrast, The Proposed Robust Semantic Framework Maintains A High And Stable Task Accuracy Even Under Severe Channel Uncertainty. The Probabilistic Constraint Transformation Ensures That The Allocated Power And Bandwidth Provide Sufficient Margin To Absorb The Channel Fluctuations. Furthermore, The Dynamic Semantic Compression Allows The System To Prioritize The Transmission Of Essential Core Features, Sacrificing Peripheral Detail To Maintain The Primary Functionality Of The Machine Service, Thus Demonstrating A Profound Resilience That Traditional Systems Lack.

5.3 Evaluation Of Multimodal Semantic Fidelity

The Evaluation Of Semantic Fidelity Specifically Highlights The Advantages Of The Multimodal Fusion Approach Utilized In This Framework. When Analyzing The Performance Of The

Autonomous Navigation Service Under Varying Environmental Conditions, The Fusion Of Visual And Radar Semantics Proves Critical. In Simulated Clear-Weather Conditions, The High-Resolution Visual Semantics Dominate The Feature Space, Enabling Precise Object Classification. However, When Simulated Weather Impairments (Such As Heavy Rain Or Fog) Are Introduced, Reducing The Efficacy Of The Visual Sensors, The Cross-Attention Mechanism Dynamically Reweights The Latent Space To Favor The Radar-Derived Spatial Semantics. Although The Classification Confidence Drops, The Spatial Awareness Required For Collision Avoidance Remains Perfectly Intact. The Robust Resource Allocation Algorithm Continuously Monitors These Shifts In Semantic Weighting And Adjusts The Transmission Parameters Accordingly. It Was Observed That Maintaining The Fidelity Of Radar-Heavy Semantic Vectors Requires Different Power Profiles Compared To Visual-Heavy Vectors Due To The Structural Differences In Their Latent Representations. The Ability Of The Network Controller To Discern These Differences And Allocate Resources Tailored To The Instantaneous Multimodal Composition Of The Data Represents A Significant Advancement Over State-Of-The-Art Methods, Ensuring That Heterogeneous Quality-Of-Service Demands Are Not Merely Met On Average, But Are Consistently Satisfied Across The Dynamic Operational Envelope Of The Machines.

6. Conclusion And Future Directions

6.1 Summary Of Contributions

This Paper Has Presented A Comprehensive Investigation Into The Deployment Of Semantic Communication For Multimodal Machine Services Within Integrated Sensing And Communication Networks. The Core Challenge Of Operating Sophisticated Semantic Extraction Models Under The Severe Constraints Of Imperfect Channel State Information And Heterogeneous Quality-Of-Service Demands Was Systematically Addressed. By Formulating A Joint Optimization Framework That Intertwines Robust Resource Allocation With Dynamic, Environment-Aware Semantic Compression, The Study Demonstrates A Viable Pathway Toward Resilient Next-Generation Machine-Type Communications. The Theoretical Models Established How Probabilistic Constraints Can Effectively Bound The Uncertainties Introduced By Imperfect Channel Estimates, Safeguarding The Transmission Of Critical Multimodal Latent Vectors. Extensive Performance Evaluations Corroborated The Theoretical Design, Revealing That The Proposed Robust Semantic Framework Significantly Outperforms Traditional Bit-Level Communication Architectures And Non-Robust Semantic Baselines. It Provides Superior Task Accuracy, Lower End-To-End Latency, And Exceptional Stability Across Varying Degrees Of Network Stress And Environmental Degradation, Thereby Proving Its Efficacy For Mission-Critical Autonomous Systems.

6.2 Open Challenges And Forward Outlook

While This Research Establishes A Robust Foundation, The Integration Of Semantic Communication And Sensing Networks Remains An Expansive Field With Numerous Unresolved Challenges. Future Research Must Address The Computational Bottlenecks Associated With Running Deep Multimodal Semantic Extraction Networks On Highly Constrained Edge Devices, Potentially Exploring Techniques Such As Neuromorphic Computing Or Extreme Network Quantization. Additionally, The Scalability Of The Robust Resource Allocation Algorithm Needs Further Refinement; As The Density Of Machine Devices Scales Into The Thousands Per Cell, Centralized Optimization Approaches Will Become Computationally Prohibitive. Exploring Distributed, Multi-Agent Reinforcement Learning Techniques For Decentralized Resource

Management Offers A Promising Direction. Finally, Establishing Standardized, Task-Agnostic Metrics For Semantic Information Remains A Profound Theoretical Challenge That Must Be Overcome To Facilitate Interoperability Between Diverse Semantic Communication Equipment And Networks [24]. Addressing These Challenges Will Be Crucial For Realizing The Full Potential Of Intelligent, Autonomous, And Seamlessly Connected Machine Ecosystems.

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