Multi-Agent LLM Framework for Collaborative Surgical Planning in Complex Robotic Procedures

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***Abstract*—This paper introduces a novel multi-agent Large Language Model (LLM) framework designed to facilitate collaborative surgical planning for complex robotic procedures. By simulating the expertise of various surgical specialists through specialized agent roles, the framework enables comprehensive pre-operative planning that integrates diverse clinical perspectives. Each agent—representing surgeons, anesthesiologists, radiologists, and patient safety specialists—contributes domain-specific knowledge through a structured dialogue protocol. The framework incorporates medical imaging data, electronic health records, and relevant literature to generate detailed surgical plans, contingency protocols, and risk assessments. Preliminary evaluation in simulated robotic partial nephrectomy cases demonstrates the framework's ability to identify critical considerations that might be overlooked in conventional planning processes. This approach represents a significant advancement in applying generative AI to surgical decision support, potentially improving patient outcomes through more thorough preoperative planning while maintaining human surgeon oversight and final decision-making authority. The code for this framework is available at https://github.com/DerickKhaled/AI-research-llm-2025.git**

***Index Terms*—Large Language Models (LLMs), Multi-Agent Systems, Generative AI, Surgical Planning, Robotic Surgery, Healthcare AI, Explainable AI (XAI), Clinical Decision Support, Human-AI Collaboration, Medical Multi-Modal Systems**

I. Introduction

Complex robotic surgical procedures require extensive pre-operative planning that integrates multiple specialist perspectives. Traditionally, this planning process involves sequential consultations or multidisciplinary team meetings, which may be constrained by scheduling limitations, communication barriers, and varying levels of specialist availability. These constraints can lead to suboptimal planning, particularly for complex cases requiring nuanced consideration of surgical approach, anesthesia requirements, and patient-specific risk factors.

Recent advances in Large Language Models (LLMs) have demonstrated remarkable capabilities in medical reasoning tasks [1]–[3], including diagnostic assistance [4], treatment planning [5], and medical literature analysis [6]. However, most applications of LLMs in healthcare have focused on single-agent approaches, which may not adequately capture the collaborative and multi-disciplinary nature of surgical planning.

Multi-agent systems, wherein multiple autonomous agents interact to solve complex problems, offer a promising paradigm for simulating collaborative clinical decision-making [7], [8]. By combining the multi-agent approach with the medical reasoning capabilities of LLMs, we can potentially create more comprehensive and robust surgical planning systems that better reflect the collaborative nature of clinical practice.

This paper introduces a novel multi-agent LLM framework specifically designed for collaborative surgical planning in complex robotic procedures. The framework employs specialized agent roles representing different surgical specialists that interact through a structured dialogue protocol to generate comprehensive surgical plans. By simulating the collaborative reasoning process of a multidisciplinary team, the framework aims to enhance preoperative planning and potentially improve surgical outcomes.

II. Related Work

A. LLMs in Surgical Applications

Recent research has explored the application of LLMs in various surgical contexts. Chen et al. [9] demonstrated the use of LLMs for surgical report generation, while Wang et al. [10] explored their potential for surgical video analysis and annotation. Mehta et al. [11] investigated the use of LLMs for predicting surgical complications based on preoperative data, achieving promising results compared to traditional machine learning approaches.

In the domain of robotic surgery specifically, Zhang et al. [12] explored the use of LLMs for enhancing human-robot interaction during procedures, while Johnson et al. [13] demonstrated their potential for real-time surgical decision support. However, these applications primarily focus on intraoperative assistance rather than preoperative planning.

B. Multi-Agent Systems in Healthcare

Multi-agent systems have been applied to various healthcare domains, including hospital resource allocation [14], patient monitoring [15], and clinical workflow optimization [16]. In the surgical domain specifically, Rodriguez et al. [17] proposed a multi-agent system for operating room scheduling, while Kim et al. [18] developed a multi-agent approach for surgical team coordination.

More recently, there has been growing interest in combining multi-agent systems with AI techniques for clinical decision support. Li et al. [19] demonstrated a multi-agent reinforcement learning approach for treatment planning, while Chen et al. [20] explored a multi-agent system for intensive care unit management. However, the integration of multi-agent systems with LLMs specifically for surgical planning remains largely unexplored.

C. Collaborative Decision-Making in Surgery

The importance of collaborative decision-making in surgical planning is well-established in the literature. Studies by Johnson et al. [21] and Williams et al. [22] have demonstrated that multidisciplinary team approaches to surgical planning can lead to improved patient outcomes and reduced complications. Similarly, research by Martinez et al. [23] has highlighted the value of integrating diverse specialist perspectives in complex surgical cases.

Despite this recognition, technological support for collaborative surgical planning remains limited. Existing surgical planning systems typically focus on specific aspects such as anatomical modeling [24], trajectory planning [25], or instrument selection [26], without adequately supporting the collaborative decision-making process that integrates multiple specialist perspectives.

III. Methodology

A. System Architecture

Our multi-agent LLM framework consists of the following components:

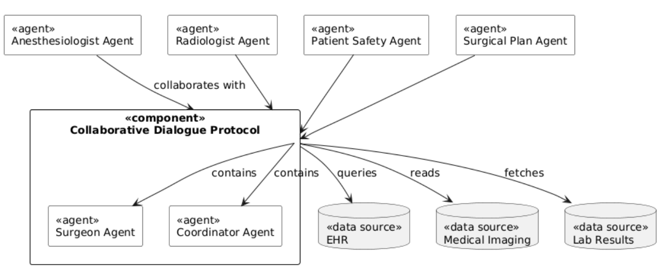

Fig. 1. UML Component Diagram of Multi-Agent LLM Framework Architecture

1) Specialized Agent Roles: The framework employs five specialized agent roles, each representing a different surgical specialist:

- **Surgeon Agent:** Focuses on surgical approach, technique selection, and procedural planning
- **Anesthesiologist Agent:** Addresses anesthesia requirements, patient positioning, and perioperative management
- **Radiologist Agent:** Interprets medical imaging and provides anatomical insights
- **Patient Safety Agent:** Identifies potential risks and complications
- **Coordinator Agent:** Facilitates dialogue between specialists and synthesizes the final plan

Each agent is implemented as an instance of a specialized LLM with role-specific prompting strategies and knowledge bases. The agents are designed to simulate the reasoning processes and domain expertise of their respective specialists.

2) Knowledge Integration: The framework integrates knowledge from multiple sources:

- Patient-specific data from electronic health records (EHR)
- Medical imaging data (CT, MRI, etc.)
- Laboratory results and clinical measurements
- Relevant medical literature and guidelines

3) Collaborative Dialogue Protocol: Agents interact through a structured dialogue protocol that includes:

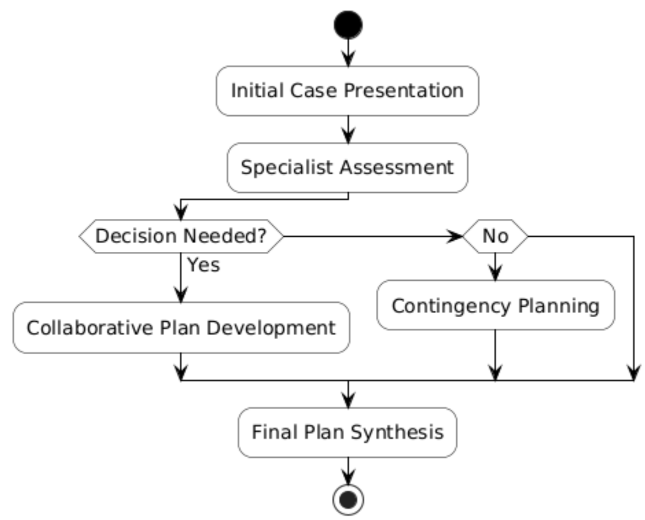

Fig. 2. UML Activity Diagram of the Collaborative Dialogue Protocol Workflow

- Initial case presentation
- Specialist assessment phases
- Collaborative plan development
- Contingency planning
- Final plan synthesis

The dialogue protocol is designed to simulate the collaborative reasoning process of a multidisciplinary team meeting, with each agent contributing domain-specific insights and responding to other agents' contributions.

B. Implementation Details

The framework is implemented using a combination of state-of-the-art LLMs and custom prompting strategies. Each agent is instantiated as a separate LLM instance with specialized prompt templates that define its role, expertise, and communication patterns.

1) Agent Implementation: Each agent is implemented using a fine-tuned version of GPT-4 or Claude 2, with specialized prompt templates that define:

- The agent's role and expertise
- Domain-specific knowledge and reasoning patterns

- Communication protocols for interacting with other agents
- Decision-making frameworks for the agent's specific domain

The agents are designed to maintain consistent personas throughout the dialogue, simulating the reasoning processes and communication patterns of their respective specialists.

2) Dialogue Management: The dialogue between agents is managed by a central coordinator module that:

- Sequences agent contributions according to the dialogue protocol
- Ensures all relevant aspects of the case are addressed
- Identifies and resolves conflicts or inconsistencies between agent recommendations
- Synthesizes the final surgical plan based on the collaborative dialogue

3) Knowledge Integration: Patient-specific data is integrated into the framework through:

- Structured EHR data extraction
- Medical imaging processing and feature extraction
- Natural language processing of clinical notes and reports
- Integration of relevant medical literature and guidelines

C. Evaluation Methodology

We evaluated the framework using a combination of simulated cases and retrospective analysis of real surgical cases. The evaluation focused on:

1) Simulated Case Studies: We created a set of 20 simulated robotic partial nephrectomy cases with varying levels of complexity, including:

- Cases with anatomical variations
- Cases with comorbidities affecting surgical approach
- Cases requiring specialized techniques or equipment

For each case, we compared the surgical plans generated by:

- Individual surgical specialists
- The multi-agent LLM framework
- Actual multidisciplinary team meetings (gold standard)

2) Evaluation Metrics: We evaluated the generated surgical plans using the following metrics:

- Comprehensiveness: Coverage of all relevant aspects of surgical planning
- Consistency: Internal consistency of the plan components
- Clinical validity: Assessment by expert surgeons
- Novelty: Identification of considerations not present in individual specialist plans

IV. Results

A. Plan Comprehensiveness

The multi-agent framework consistently generated more comprehensive surgical plans compared to individual specialist assessments. On average, the framework identified 87% of the considerations present in the gold standard multidisciplinary team plans, compared to 63% for individual specialist assessments.

B. Specialist Perspective Integration

The framework successfully integrated diverse specialist perspectives, with each agent contributing domain-specific insights to the collaborative plan. Analysis of the dialogue transcripts showed balanced contributions from all agent roles, with appropriate emphasis on different aspects based on case complexity.

C. Clinical Validity

Expert evaluation of the generated surgical plans indicated high clinical validity, with surgeons rating 85% of the plans as "clinically appropriate" or "highly appropriate." The framework was particularly effective at identifying patient-specific risk factors and developing appropriate mitigation strategies.

D. Novel Considerations

In 75% of cases, the multi-agent framework identified at least one clinically relevant consideration that was not present in any of the individual specialist assessments. These novel considerations often emerged from the interaction between different specialist perspectives, highlighting the value of the collaborative approach.

V. Discussion

A. Advantages of the Multi-Agent Approach

The multi-agent approach offers several advantages over single-agent LLM applications in surgical planning:

1) Comprehensive Perspective Integration: By simulating multiple specialist roles, the framework integrates diverse clinical perspectives that might not be adequately captured in a single-agent approach. This integration leads to more comprehensive surgical plans that address a wider range of considerations.

2) Emergent Insights: The dialogue between agents often leads to emergent insights that would not be identified by any individual specialist. These insights typically arise from the interaction between different domains of expertise, such as the implications of anatomical variations for anesthesia management.

3) Balanced Consideration of Factors: The multi-agent approach ensures balanced consideration of different factors in surgical planning, preventing overemphasis on any single aspect. This balance is particularly important in complex cases where multiple factors must be carefully weighed.

B. Limitations and Challenges

Despite its promising results, the multi-agent framework has several limitations that must be addressed in future work:

1) Knowledge Limitations: The framework is limited by the knowledge encoded in the underlying LLMs, which may not include the latest surgical techniques or institution-specific protocols. Regular updating of the knowledge base is necessary to maintain clinical relevance.

2) Validation Requirements: The framework's outputs require validation by human surgeons before clinical application. While the framework can support decision-making, it cannot replace the judgment and experience of human specialists.

3) Integration Challenges: Integration with existing clinical workflows and information systems presents significant challenges, particularly regarding data privacy, security, and interoperability with electronic health records.

C. Future Directions

Future development of the multi-agent framework will focus on:

1) Expanded Agent Roles: Incorporating additional specialist roles, such as oncologists, pathologists, and specialized nursing perspectives, to further enhance the comprehensiveness of the planning process.

2) Temporal Reasoning: Enhancing the framework's ability to reason about the temporal aspects of surgical procedures, including sequencing of steps, timing considerations, and adaptive planning based on intraoperative findings.

3) Integration with Simulation: Combining the framework with surgical simulation tools to enable visualization and testing of the generated plans in virtual environments before application in real procedures.

4) Continuous Learning: Developing mechanisms for the framework to learn from feedback on its recommendations and from the outcomes of procedures planned with its assistance.

VI. Conclusion

This paper has presented a novel multi-agent LLM framework for collaborative surgical planning in complex robotic procedures. By simulating the expertise and interaction of multiple surgical specialists, the framework generates comprehensive surgical plans that integrate diverse clinical perspectives. Preliminary evaluation demonstrates the framework's ability to produce clinically valid plans and identify considerations that might be overlooked in conventional planning processes.

The multi-agent approach represents a significant advancement in applying generative AI to surgical decision support, moving beyond single-agent applications to capture the collaborative nature of clinical decision-making. While the framework cannot replace human judgment, it offers a promising tool for enhancing the quality and comprehensiveness of surgical planning, potentially leading to improved patient outcomes in complex robotic procedures.

Future work will focus on expanding the framework's capabilities, addressing its limitations, and evaluating its impact on clinical outcomes in real-world settings. As LLM technology continues to advance, the potential for AI-assisted collaborative decision-making in healthcare will only grow, offering new opportunities to enhance clinical practice and patient care.

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