Predicting Optimal Intervention Timing in Mixed Reality Collaboration

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1 Introduction and Problem Statement

In mixed reality (MR) [1], participants continuously interact through speech, movement, and shared attention. When these behaviors fall out of balance, such as one member dominating or others losing focus, collaboration efficiency decreases. Our research question is: **Can we predict optimal moments for system-guided interventions to improve collaborative task efficiency in MR environments?**

Knowing when to intervene is crucial for designing adaptive MR systems that assist rather than interrupt teamwork. By detecting early signs of imbalance or disengagement, the system can suggest timely actions such as redistributing attention, encouraging quieter members to speak, or refocusing shared attention on the task. Such data-driven intervention timing can significantly improve collaboration in education, remote work, and training applications.

2 Technical Approach and Data

We aim to model how collaboration evolves and identify when interventions should occur. Using the Multimodal Group Interaction Dataset, which includes **synchronized pairwise features** (e.g., speaking entropy, dominance ratio, joint attention), **network metrics** (e.g., density, reciprocity, eigenvector centrality), and **task performance data** (e.g., completion time, interaction logs), we can link behavioral dynamics to teamwork outcomes. Our workflow includes:

- **Feature Engineering**
  We aggregate and normalize pairwise interaction and session-level network metrics from the multimodal dataset. These capture both micro-level behaviors (communication balance, proximity, shared attention) and macro-level coordination patterns, enabling the model to connect individual dynamics with collective performance.
- **Modeling**
  For multiple approaches, we will compare them to balance interpretability and accuracy.
  - Temporal trend analysis using **Hidden Markov Models** (HMMs) or **Long Short-Term Memory** (LSTM)[2] for state transitions in group coordination. HMMs provide interpretable probabilistic state transitions, revealing when a team shifts from balanced to imbalanced interaction. LSTMs can learn long-term temporal dependencies, capturing gradual coordination loss that may precede performance drops.
  - Supervised learning such as **Random Forest**[3] and **XGBoost** classifiers to label time windows as stable or intervention-needed. These models are robust to noisy behavioral data and yield feature importance scores, helping us identify which cues most strongly predict coordination breakdowns.
  - Network analytics[4] (via **NetworkX** and **statsmodels**) to link behavioral shifts with collaboration outcomes. Metrics like density, reciprocity, and centrality reflect cohesion and equality; drops in these indicate dominance or disengagement, where system assistance is valuable.
- **Evaluation**
  The predicted intervention windows will be validated against task performance metrics such as completion time and interaction diversity. Model performance will be evaluated by **accuracy**, **F1 score**, and **correlation analysis** to assess how well predictions anticipate low-collaboration periods.

References

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