BioSyncHRI

Synchronizing Human Robot Interaction via Real-Time Biosignal Adaptation

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Abstract

Virtual reality (VR) surgical simulators, such as the Da Vinci Skills Simulator, are well-established tools that improve surgical performance and patient outcomes. However, current human-robot interactions in these systems are based entirely on behavioral data, without incorporating critical physiological signals such as surface electromyography (sEMG) for stress detection, electroencephalography (EEG), heart rate variability (HRV), and emotional state analysis. This study builds on a pilot investigation that successfully measured neuromarkers during VR-simulated surgery. We extend this work by integrating real-time biosignal-driven adaptive systems into VR simulators, enabling robots to learn directly from the operator's feedback, interpret, and respond to physiological signals. By dynamically adapting to different mental and physical states, this approach aims to enhance surgeons' mental health, optimize performance, reduce fatigue and burnout, and ultimately improve surgical outcomes.

CCS Concepts

• **Human-centered computing** → **Interaction techniques**.

Keywords

Biosignal Processing, Adaptive Robotics, Robotic Surgery, Human-Robot Interaction, Virtual Reality Simulation, Machine Learning

1 Introduction

Human-Robot Interaction (HRI) is increasingly recognized for its transformative potential across multiple domains, particularly healthcare and robot-assisted surgery [13] where robots reduce complication risks and improve recovery times for patients [21]. To capitalize on the potential of HRI, virtual reality (VR) robotic surgical simulators are becoming widely applied in hospitals as training platforms for surgeons, enabling them to refine their technical skills in highly controlled, risk-free environments [3, 8]. The Da Vinci Skills Simulator, which prepares surgeons for real-world procedures, is a leading system that provides an immersive, high-fidelity replication of robotic surgical workflows [6]. The Da Vinci Skills Simulator typically consists of four robotic arms (see Figure 1), operated via a master console, allowing surgeons to execute movements with enhanced dexterity, tremor filtration, and higher precision compared to traditional surgical procedures [1, 3].

Figure 1: The Da Vinci Robotic Surgery System and the surgeon's console view during surgical procedures and training exercises.

2 Related Work

A previous pilot study conducted by Baumgartner et al. [2] demonstrated that surgeons who achieved higher levels of performance and flow exhibited different neuromarkers when compared to surgeons with lower performance scores, particularly increased frontal theta activity (see Figure 2) [2]. Although these findings underscore the importance of cognitive state monitoring, this early, exploratory research was limited by a small sample size (N=20) and the absence of machine learning-based real-time adaptation.

While several other studies to date have successfully integrated multimodal biosignal monitoring, including EEG, sEMG, HRV, and eye-tracking to enhance cognitive workload assessment in robotic surgery [4, 15, 17, 19], these studies have faced other challenges in accurately interpreting EEG and HRV data. Specifically, in dealing

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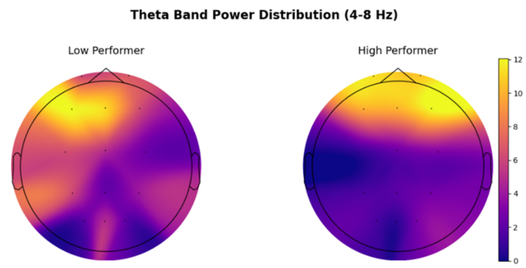

Figure 2: Topographic map from the Pilot Study "Inflow-Opera", illustrating significantly higher theta activation in the frontal regions among high-performing surgeons.

with signal noise and variability in high-pressure surgical environments. Additionally, sEMG remains underutilized, despite its potential to capture subtle stress responses, such as trapezius muscle activation—a well-documented but often overlooked physiological marker of elevated stress levels [18]. Moreover, while these studies demonstrate the feasibility of biosignal-based monitoring, current implementations do not integrate real-time adaptive feedback into surgical workflows. There is a lack of interactive systems capable of dynamically responding to biosignal fluctuations, whether through haptic adjustments, visual alerts, or automated workload modulation, limiting their practical application in real-world robotic surgery.

3 A New Approach to Adaptive Robotic Systems

In our research, we propose a novel framework that integrates multimodal biosignal data directly into the real-time control loop of the robotic system and the surgeon's console. This approach enhances adaptive human-robot interaction by continuously monitoring the surgeon's physiological and cognitive states and dynamically adjusting system responses.

Biosignals including surface electromyography (sEMG), electroencephalography (EEG), and heart rate variability (HRV) are acquired using a multimodal sensing setup. These signals are processed with an advanced deep learning framework that combines spatial and temporal feature extraction. Convolutional neural networks (CNNs) extract spatial patterns from the biosignals, while long short-term memory (LSTM) networks capture the temporal dynamics. This hybrid CNN-LSTM architecture is formulated as:

$$y_t = f_\theta\Big(\mathrm{LSTM}\big(\mathrm{CNN}(x_t)\big), h_{t-1}\Big), \tag{1}$$

where x_t denotes the biosignal input at time t, h_{t-1} is the previous hidden state, and y_t is the predicted state label (e.g., cognitive load or stress level). An attention mechanism is further integrated within the LSTM module to focus on critical temporal segments, thereby enhancing prediction reliability in noisy, high-pressure environments.

Based on the classification outcomes, the system implements adaptive feedback mechanisms in real time. For example, if sEMG data indicate muscle fatigue, the sensitivity of the robotic console is automatically reduced to lower the physical effort required for control. Likewise, if EEG and HRV analyses reveal signs of cognitive fatigue or stress, on-screen feedback—such as break recommendations or visual guidance cues—is provided directly at the surgeon's console.

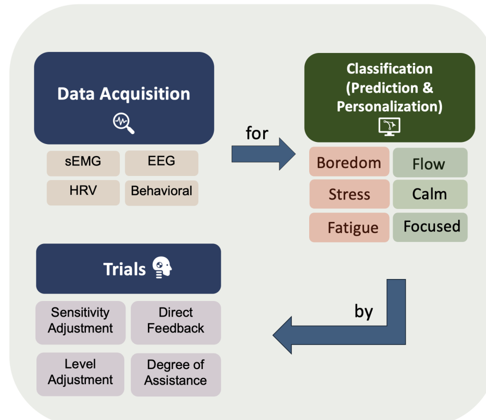

Figure 3: The protocol begins with data acquisition, advances to state classification, and culminates in four-mode real-time feedback.

Furthermore, the robotic system adjusts the level of assistance dynamically. Enhanced guidance, such as highlighting subsequent procedural steps or suggesting optimal cutting points, is provided based on the surgeon's real-time state. During training simulations, exercise difficulty can be automatically modulated to maintain an optimal cognitive workload and engagement level.

One way to implement such an adaptive system is by integrating reinforcement learning into the existing framework. Specifically, a deep Q-network (DQN) can be employed to learn optimal control policies that balance surgical performance and operator comfort. A DQN is particularly effective at handling real-time sequential decision-making in environments with discrete action spaces [22]. Under this approach, the DQN learns by estimating the state-action value function [23]:

$$Q(s, a; \theta) = \mathbb{E}\left[\sum_{k=0}^{\infty} \gamma^k r_{t+k} \,\middle|\, s_t = s, a_t = a\right], \tag{2}$$

where s represents the current biosignal-informed state, a denotes a potential action (e.g., adjusting console sensitivity or issuing a break prompt), r_t is a reward function that reflects both task performance and physiological well-being, γ is the discount factor, and θ are the network parameters. By ongoing policy updates, the reinforcement learning component enables the system to autonomously refine its adaptive strategies over time.

Via integration of these deep learning and reinforcement learning methodologies, our adaptive robotic system achieves a nuanced interpretation of multimodal biosignals and dynamically refines its interaction strategies in real time. This comprehensive framework not only enhances surgical precision and training efficiency but also serves as a safeguard against fatigue and burnout, ultimately contributing to improved long-term operator well-being.

Figure 4: Positive, real-time feedback derived from both behavioral data and biosignals.

Figure 5: Timely, corrective feedback and attention cues derived from both behavioral data and biosignals.

4 Conclusion

In conclusion, biosignal-driven adaptation in robotic-assisted surgery holds promise for revolutionizing human-robot collaboration. Leveraging real-time feedback from EEG, HRV, and sEMG can create more adaptive systems that enhance performance, reduce stress-induced fatigue, and enhance training experiences. This work contributes to the HRI/HCI field by advancing adaptive interfaces, improving cognitive ergonomics, and integrating affective computing strategies. Future research directions should focus on refining multimodal biosignal classification models, incorporating reinforcement learning, and conducting iterative usability evaluations to optimize robotic responses in dynamic surgical and assistive environments.

5 Limitations and Critique

Despite these promising advances and first studies in the field of HRI and adaptive systems, several limitations remain. Variability in biosignal quality—due to sensor placement, environmental noise, and individual differences—poses challenges for consistent classification. The computational complexity of processing high-dimensional biosignal data in real time may restrict scalability. Addressing these challenges will require interdisciplinary collaboration, further user-centered evaluations, and iterative design refinements to fully realize the potential of bioadaptive robotic systems in HCI contexts. From an operator's perspective, the ethical implications of continuous physiological monitoring warrant critical attention. While these technologies aim to enhance performance and well-being, they may also lead to increased surveillance and potential misuse of personal data. Users might feel pressured to suppress signs of stress or fatigue for fear of negative evaluations, which could undermine trust and create an environment of over-surveillance. It is essential that the deployment of such systems is accompanied by transparent policies, clear safeguards for data privacy, and measures that prioritize users' autonomy and well-being over purely performance-driven metrics. Addressing these ethical challenges will require interdisciplinary collaboration, user-centered evaluations, and ongoing dialogue to ensure that bioadaptive robotic systems serve both organizational goals and the rights of the individual user. Furthermore, while our existing methodology, incorporating machine learning and reinforcement learning, enables real-time adaptation, it may fall short when dealing with large or continuous action spaces or highly varied user populations. Future work could explore more advanced policy optimization algorithms or meta-learning techniques to enhance scalability and personalization in evolving surgical environments.

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