Psychophysiological Data and Computer Vision to Assess Cognitive Load and Team Dynamics in Cardiac Surgery

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1 Purpose

The cardiac operating room (OR) is a high-risk environment where several specialized providers work as team to provide care for patients undergoing complex surgical procedures. Cardiac surgery can be conceptualized as a team-based sociotechnical system with critical requirements for communication and coordination. Contemporary research in this realm has moved away from the individual as the unit of cognitive analysis, and a new focus on the activity system (human actors, their tools and the environment) has been proposed; this framework has been referred to as "distributed cognition".[1] To execute highly specialized tasks, resources are distributed throughout the OR team, as well as the cognitive demands imposed by the surgical tasks. Furthermore, the dynamics of team activities may provide relevant information for understanding the multitude of factors that impact surgical performance and patient safety outcomes.[2] Previous research has shown that certain patterns extracted from team members' position and motion data can predict team coordination and cohesion..[3] In this pilot study, we describe a novel integrative approach that captures objective measures of team cognitive load (heart rate variability), as well as position and motion metrics from multiple OR team members generated by a computer vision system. Our aim was to investigate the feasibility of using this novel approach to integrate and visualize team dynamics and cognitive load metrics gathered from the OR team during a real-life cardiac surgery.

2 Methods

2.1 Study Design, Setting and Participants

We studied a cardiac surgical team during a real-life coronary-artery bypass grafting surgery (CABG). This procedure involves an open-heart surgery, requiring a highly specialized team of 6-12 providers divided into four subteams. This study was approved by the local Institutional Review Board (IRB).

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2.2 Cognitive Load Metrics (Heart Rate Variability)

Attending surgeons, anesthesiologists and perfusionists were equipped with a heart rate sensor (Polar H7 chest strap) that captures the intervals between successive heart beats (RR intervals) in milliseconds, and transmits the data, via Bluetooth connection, to a receiving station (sports watch (Polar V800). Previous research has used RR intervals as a psychophysiological measure surgeon's cognitive workload.[4] Raw data was exported in *.txt* format and analyzed in Kubios HRV (version 3.1.0), where an automatic RR artefact correction method was used to remove artefacts and ectopic beats. Artefacts were replaced with interpolated values using a cubic spline interpolation.

2.3 Team Dynamics Metrics (Position and Motion Tracking)

A GoPro Hero 4 camera (1280 x 720 pixels, 30 fps) was used to record the entire procedure. The first 5 minutes of the *Separation from Bypass* step was analyzed. This is a critical step and imposes the highest cognitive demand to the OR cardiac team.[5]

OpenPose is an open-source, deep-learning enabled computer vision system capable of detecting multiple humans and labeling up to 25 key body points using 2D video input from conventional cameras. The architecture of this system uses a two-branch multi-stage convolutional network (CNN) in which each stage in the first branch predicts confidence 2D maps of body part locations, and each stage in the second branch predicts Part Affinity Fields (PAF) which encode the degree of association between parts. Training and validation of the OpenPose algorithms were evaluated on two benchmarks for multi-person pose estimation: the MPII human multi-person dataset and the COCO 2016 keypoints challenge dataset. Both datasets had images collected from diverse real-life scenarios, such as crowding, scale variation, occlusion and contact. The OpenPose system exceeded previous state-of-the-art systems.[6] We processed the 5-minute video using this software (version 1.4.0) and exported x and y coordinates (in pixels) of the position of the neck of each OR team member, per frame, in JSON format. For each detected point a confidence score from 0 to 1 was provided based on the comparison with ground-truth data from the system's library. To measure motion, we calculated the distance (in pixels) from the team member's neck point to a stationary reference point (patient's heart) for each frame. Then, we calculated frame-to-frame change in distance, which was used to calculate the velocity (pixels/second) in which each participant moved over time. Team centrality was calculated by the distance between each team member and the patient's heart (surgical field).

2.4 Data Integration and Visualization

To integrate and synchronize position and motion data generated by the computer vision software and physiological data gathered by the heart rate sensor, we used the InterAct software (Mangold v. 16.0). A visual analytics software (Tableau v2018.1) was used to create a heat map of the position of each team member in the OR, displaying the density of the neck position over a 5-minute period.

3 Results

The analysis of the 5-minute video generated 90.000 frames, detecting 7 different people in the OR. The neck keypoint of all team members was detected in 96% of the frames, with a mean confidence score of 0.83 (standard deviation = 0.11). A heat map plotting the density of people's position is shown in Fig. 1.

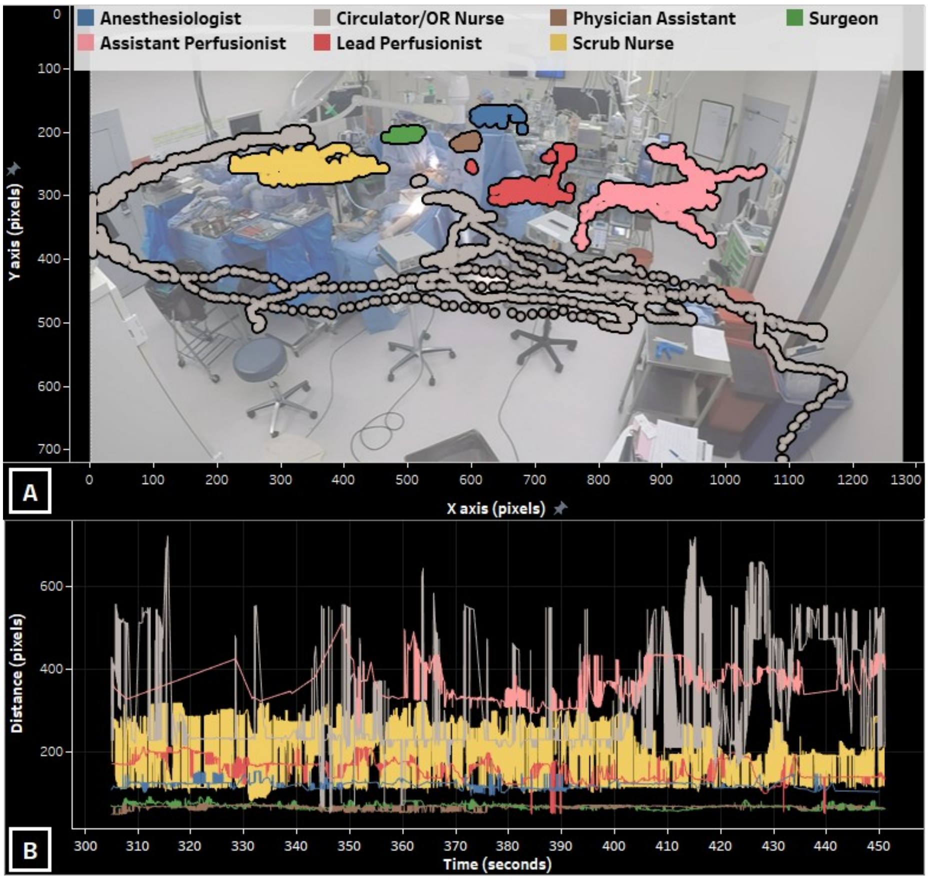

Fig. 1. Density of individual's position (A), and team centrality (B) measured by the distance between each team member and the patient's heart (surgical field) during *Separation from Bypass.*

The processed video was overlaid with team members' skeletons (See supplemental video) and synchronized with the physiological signals (RR intervals) and motion metrics (neck keypoint velocity) of the core cardiac team members. This integrated view allows the simultaneous analysis of team dynamics and cognitive load. (Fig. 2)

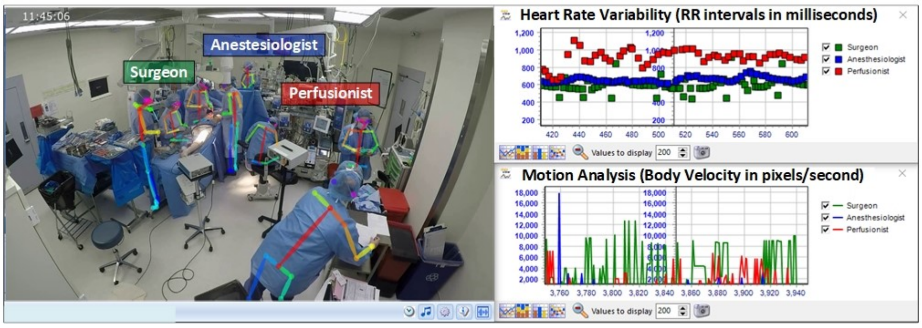

Fig. 2. Integrated visualization of motion tracking, cognitive load and team dynamics metrics.

4 Conclusion

This pilot study demonstrates the feasibility of a novel integrative approach to capture team cognitive load and team dynamics metrics during complex surgical procedures. This approach uses heart rate variability as an objective and unobtrusive measure of cognitive load and a deep learning-based system that performs multi-person pose estimation from videos recorded with regular cameras. The main novelty of the proposed approach is its ability to monitor in real-time the cognitive load imposed by the surgical tasks to the OR team members while simultaneously capturing relevant spatial relationships between team members, the patient and medical devices in the OR environment. Future studies can use similar approach to investigate the relationship between team cognitive load, team dynamics metrics and surgical patient outcomes.

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