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Teaming with aerial systems: cognitive load assessment

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ABSTRACT

Multi-robot systems adoption is increasing for disaster response, industry, and transport and logistics. Nevertheless, humans will remain indispensable to control and manage these fleets of robots, and particularly so in safety-critical applications. However, more sophisticated AI techniques creates unintelligible robot control programs that are not necessarily human-centered. Furthermore, a human operators' cognitive capacities are challenged (and eventually exceeded) as the sizes of autonomous fleets grow. Our goal is to assess various means of measuring the operators cognitive load in an exploration task with six UAVs.

METHOD

Successful experiments on fully autonomous decentralized fleets of robots are nowadays frequent, and our group conducted many over the years, but assessing the ease of operating these systems is challenging. We address this question by measuring the cognitive load of the operators: with subjective metrics such as the NASA Task Load Index (NASA TLX) and with psychophysiological measures such as skin conductivity, heart rate variability and pupil dilation [1].

To establish a controlled environment, we conducted our study indoors using a fleet of six micro-quadcopters with global localization. Participants were asked to stand in a designated area at the border of our flying arena. For immersion reasons, no glass or net was added between them and the flying arena. Four conditions were tested in this study, controlling the fleet from: 1. a tablet using waypoints, 2. a tablet using a self-deployment algorithm, 3. a tangible interface using waypoints, and 4. a tangible interface using a self-deployment algorithm.

The goal of each of the four missions was to find as many hidden ground features (simulated) as possible in the flying area. In the tablet/self-deploy condition participants manipulated a user interface on a tablet to assign one or two markers around which the UAVs distributed themselves autonomously. When in the tablet/waypoint condition, participants again used a tablet but assigned a position to each UAV individually. Commands were entered into the interface and transmitted to the fleet when the participant pressed a "send" button. In the tangible interface setting, UAVs were controlled using tabletop robots (3cm diameter, 5cm height) that replicated the movements of the robots in the flying arena. When using the tangible/self-deploy control mode, one or two yellow tabletop robots (used to input a region of interest) were picked up and placed at the desired location around which the UAVs distributed themselves evenly. In the tangible/waypoint condition, each UAV was controlled by moving and holding its respective table top robot to the desired location until the command had been received (indicated by LED lights changing colors), once released the tabletop robot mimicked the movement of the UAV.

The experiment was performed on 40 participants. All participants (F: 13 M: 27 Age: 18-55) were able to conduct the four missions. After each of the four experiments, participants were asked to fill the survey inspired partially by the work of [2] merged with the classic NASA TLX for self-assessment of their interaction.

Measurements

On top of the surveys, several objective measurements were gathered as shown in Fig. 1.

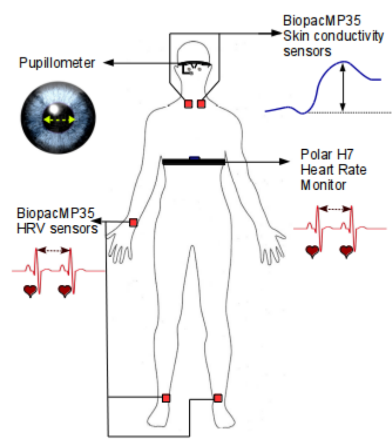

Figure 1: Sensor placement positions for the cognitive workload measures: head-mounted pupillometer, heart rate monitors (consumer grade Polar H7 and BiopacMP35 HRV), and skin conductivity sensors (BiopacMP35).

A second source of objective information is obtained from the logs of the robotic system: users actions, arena camera, features found and UAVs crashes. From the resulting dataset, we aim at validating the potential of wearables to assess the operators cognitive load. The BioPac well-established measurements are expected to relate well. The four conditions should also help validate that self-organization can help reduce the operator load.

REFERENCES

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