VIDEO-BASED ANALYSIS OF HUMAN MOTOR ACTIVITY FOR FUNCTIONAL STATE ESTIMATION

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The amount and complexity of man-machine systems are increasing dramatically. The operator often becomes the least reliable element because of their fatigue and drowsiness. Therefore, the task of monitoring human functional state, reflected in person's motor activity, is crucial. In this paper the task of aircraft pilots' functional state estimation is considered.

Introduction

Today the number and the complexity of man-machine systems are increasing. And the most of the technological failures are of anthropogenic nature. For example, the role played by human performance in aircraft accidents is shown in the Fig. 1.

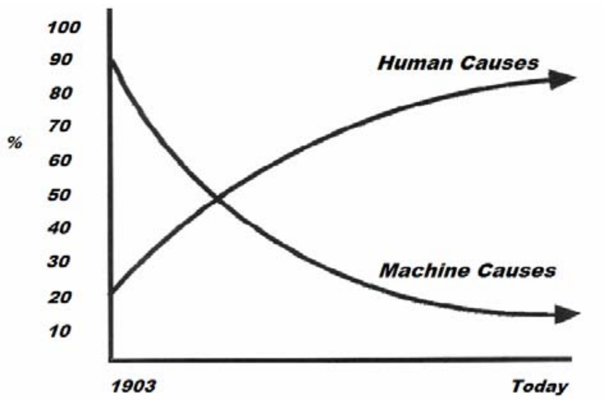

Figure 1. The role played by human performance in civil aircraft accidents [1].

The majority of accidents happen due to non-optimal human functional state, e.g. drowsiness and fatigue. It is noticed that sleepy people exhibit certain observable behaviors, including eye gaze, eyelid and pupil movements, head movement, and facial expression.

There are plenty of techniques for person functional state controlling. In general, they can be divided into two groups: intrusive (brain electrical activity, blood pressure estimation) and nonintrusive (video-based and Doppler radar-based behavioural signals estimation [2], speech analysis, interpretation of data signals from the vehicle: speed, steering position). Speaking of intrusive techniques, the most reliable correlate of sleepiness is electroencephalogram (EEG). The main disadvantages are that it is hard to measure and analyze under field conditions and its characteristic parameters are not undisputed [3]. Such parameters as pulse rate and blood pressure are shown to be suitable for determining the person's global state (alert/drowsy) [4].

Intrusive methods give precise results but require constant contact between a person and sensors in order to retrieve signals needed. Wires and sensors might be uncomfortable and obstructive which is unacceptable when doing potentially dangerous work.

Although intrusive methods are quite uncomfortable in use, they can be of particular interest when creating a training set for identifying person's non-optimal state and searching for correlates between such states and visually registered activity.

Nonintrusive techniques are currently being employed to assess humans' alertness level. Using nonintrusive methods, we can monitor visual characteristics such as blinking frequency and duration, gaze direction, head pose. Blinking frequency and duration, the size of eyelid cleft were shown to be the best oculomotor indicators for current alertness state. Saccadic speed is a reliable indicator of fatigue [3].

Subjective measures such as self-rated alertness are often used to match monitored characteristics and current functional state. A widespread 9-step Karolinska Sleepiness Scale (KSS) is used for this purpose [3].

The objective of this research is to find out certain repeatable behavioural patterns. We consider it as the first step toward development of the human functional state estimation system. Much of attention is given to the methods of informative features extraction from the video signal.

Methods

To extract repeatable behavioural patterns, a training set of images and videos depicting person's activity is required. In order to produce such a data set, seven experiments were carried out in the aircraft TU-154 pilot's cabin simulator with an option of extraordinary situations modeling (for example, weather conditions changing, engine failure). Above the first pilot's dashboard a color web-camera Logitech c910 equipped with a stereo microphone was mounted. Recorded video resolution was 640x480 px.

Before the beginning of the experiment, the adjustment procedure was conducted. To estimate the extreme points of the person's head position, the pilot was asked to look over the dashboard. To create template images of the person with their eyes closed or open, the correspondent pictures were taken.

In order to monitor long-term changes of behavioural characteristics in different flight conditions, the experiment was divided into two parts: long monotonous flight without extraordinary situations; short flight with emergency situations (engine failure or strong side wind when landing). The duration of the first period was approximately 60-90 minutes, of the second period – 8-20 minutes.

EEG and EOG (electrooculogram) electrodes were applied to the pilot before the flights. Tapping test and reaction test were taken before, after and between the flights.

After the preparations are over the flights begin. The following data are recorded: video of the pilot, pilot's EEG signals and flight protocols, which contain information about pilot's and dispatcher's actions and emergency situations.

Due to high-frequency noise in the video-signal, measuring low-amplitude parameters such as size of an eyelid cleft is impossible. Therefore, low-frequency, high-amplitude motions such as head pose variations are the most informative features in this video stream.

To estimate motor activity and to infer about human functional state, the posterior data analysis is divided into two stages: frame-by-frame analysis of the video recorded, extracting features of interest; analyzing the values obtained.

Every frame undergoes several routines: pilot's face detecting (using Viola-Jones algorithm [5]), identifying the state of an eye – open or closed (by nearest neighbors classifier using histogram of gradients description of eyes area [6]). After analyzing the sequent frame, the following values are recorded in the log-file: face detection results (1 – found, 0 – not found), face coordinates (in pixels), face size (in pixels), blinking detection result (0 – eyes opened, 1 – eyes closed).

Results

Log files containing face coordinates and blinks data were processed to find out pilots repeatable behavioural patterns and estimate their motor activity trends. Face capture percentage was the first evaluated variable. It demonstrates reliability of the face grabber. The mean of the face capture percentage during the long flights experiments ($n_1 = 4$) was 76% (the minimum value – 46%, the maximum value – 96%). The mean of the face capture percentage during the short flights experiments ($n_2 = 3$) was 84% (the minimum value – 54%, the maximum value – 99%). Due to insufficient lighting, wide range of pose variations, occlusions, caused by EOG electrodes and glasses, this percentage varies. The low precision in blinking detection was observed by the same reasons. Therefore, pose variations such as face size and coordinates were the most informative behavioural signals in this series of experiments.

Pilots pose dynamics within long and short flights was examined to find out repeatable behavioural patterns. The most stable patterns were detected in the face size dynamics, which depends on the distance between the face and the camera. Two examples of the face size variations during aircraft takeoff and climbing are shown in the Fig. 2. There is a specific trend of the pilots moving away from the camera.

Another repeatable behavioural trend of the pilot moving towards the camera was detected while landing (Fig. 3).

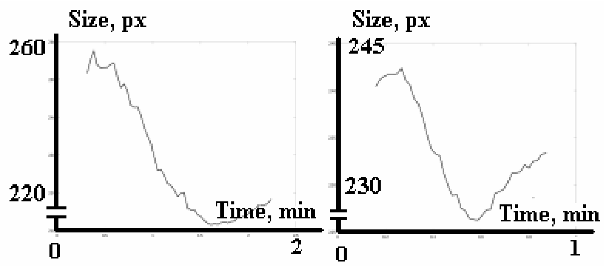

Figure 2. Two examples of the face size dynamics during takeoff and climbing of the plane.

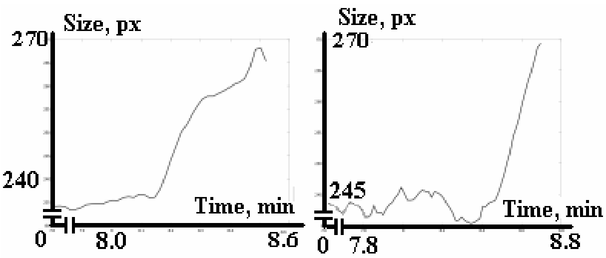

Figure 3. Two examples of the face size dynamics during landing of the plane.

The flight was divided into four parts in proportions: 20% of flight duration (takeoff and the beginning of the flight), 30% – the first part of the flight, 30% – the second part of the flight, 20% – the end of the flight and landing. The behavioural trends within these intervals were compared with each other. Face horizontal coordinate standard deviation was considered as an integral indicator of motor activity. The mean of this value within the first parts of the flights was 15.7±2.4 px, the seconds – 9.3±2.3 px, the thirds – 11.3±2.8 px, the fourths – 19.5±2 px. According to this results face pose standard deviation was the lowest within the second stage of the flight. Therefore, motor activity level was the lowest. The fourth flight part (landing) was the most active stage.

The face pose standard deviation over the long flights was 18.3±0.6 px, the short flights – 15±2.6 px. Thus, the difference between motor activity intensities over the long and the short flights was insignificant.

Conclusion

The human motion analysis techniques for functional state estimation were described. The techniques were tested within the task of pilot’s functional state estimation. The standard deviation of face horizontal coordinate was analyzed as the attribute of motion activity intensity. Repeatable motion patterns and significant contrasts between motion parameters in the different parts of the flight were detected. In particular, the highest level of pilots motor activity was detected during landing, the lowest – was observed after climbing. Deviations from repeatable behavioural patterns were considered as indicators of unusual and possibly non-optimal functional state.

Acknowledgments

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