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***Abstract*—The aim of this paper is to present an extensive neurophysiological study of the Air-Traffic-Controllers (ATCos) during *en route ATC* simulations. In other words, the purpose was to extract neurophysiological features suitable for evaluate the learning progress and for estimate in real-time the user's workload level. In collaboration with ENAC (Toulouse, France), a task specific for the en-route ATCo has been developed and tested. The subjects have been asked to learn how to complete the task within a training period of a week and, in the second week, to execute it under different difficulty levels. During the experiments, the Electroencephalogram (EEG), the Electrocardiogram (ECG), the Electrooculogram (EOG), the behavioral data and the perception of the workload (NASA-TLX) have been collected. The results showed that the frontal theta power spectral density (PSD), the parietal alpha PSD, the heart rate (HR) and the eyeblinks rate (EBR) are reliable features by which evaluating the learning progress and the user's workload. It has been demonstrated that it could be possible i) to quantify how well the subjects complete a task, and ii) to compare subject's performances, in terms of cognitive resources. In addition, it has been presented i) a system able to significantly differentiate three workload levels, and ii) how the subjective features used for the workload evaluation remain stable over the time.**

Keywords-EEG; ECG; EOG; Cognitive Learning; Training Assessment; Workload; ATM; ATC.

I. INTRODUCTION

Most research has focused on identifying characteristics of the air traffic picture that create task demand for ATCos (e.g., [1]-[4]). Others argue that there is no simple linear relationship between task demand and workload (e.g., [5], [6]). Several current research groups agree with Sperandio's [7] view that a relationship between task demand and workload can be better understood by considering how ATCos use strategies to manage their resources and regulate their workload [1], [8], [8]-[11]. Factors such as skills, training, experience, fatigue and other "stressors" all mediate the relationship between task demands, safety and performance of the ATCo. Hence, it is easy to understand how quantitative information about skills level and mental states could help to evaluate ATCos' workload level and to decide if they might need more training before working into real environments. Several studies described the correlation of spectral power of the EEG bands with the complexity of the task that the subjects are performing [12]. In fact, an increase of electroencephalographic (EEG) power spectral density (PSD) especially over the frontal cortex in the theta band (4 - 7 Hz) and a EEG PSD decrease in the alpha band (8-12 Hz) over the parietal cortex have been observed when the required mental workload, the task's complexity, the amount of information processing increase. Furthermore, it has been suggested that an increased Heart Rate (HR) could be related with an increased mental workload and engagement, while the eyeblinks duration and frequency are inversely correlated with the increase of the mental workload and attention [12]. The hypotheses of the study are that i) as the EEG theta PSD increases and the EEG alpha PSD decreases with these aspects of the task, at the end of the training period such variations should be lower than in the first session, therefore such trends could be taken as indexes of the correct acquisition of procedural skills, ii) the combined use of EEG features and HR can be used for the real-time evaluation of the operator's workload level, in a real ATM scenario involving trained subjects by defining neurophysiological WL indexes, one derived by the EEG signal (W_{EEG}), one by the ECG signal (W_{HR}) and the other by the combination between them (W_{Fusion}). Such hypotheses have been tested on a group of subjects who succeeded in the 5-days-training-period and who were then asked to execute the experimental task under different difficulty levels in order to check the workload variations by analyzing their neurophysiological signals.

II. METHODS

A. Experimental subjects and ATM simulation task

A group of six healthy volunteers has been selected in terms of age (21±4 years) and previous computer game skills. The subjects have been asked to learn to execute correctly an ATM task (LABY), that never did before, under easy (E), medium (M) and hard (H) conditions, randomly selected and proposed to them. The LABY microworld is a functional simulation of Air Traffic Control (ATC) that captures the underlying processes involved in electronic air traffic management with a simplified version of the operational human-machine interface. Microworlds are computer-based human-in-the-loop simulation environments that offer testing, behavioural/physiological measurement, and training capabilities, with the flexibility to build various scenarios [13], [14]. LABY is a dynamic environment whereby a controller must issue directional commands to guide aircraft along a predetermined route, whilst avoiding potential conflicts and dealing concurrently with other incoming information. The LABY microworld is based upon the main task of guiding *N* plane(s) around a predetermined route, indicated by a green path (Fig. 1). Participants must input numerical values such as heading, flight level, speed, etc., in order to direct flight around the trajectory and to avoid any conflicts or obstacles which may occur during the flight-route. Penalties are applied if the aircrafts deviate off the route or if other constraints are not met. The difficulty of the task can be altered according to how many aircrafts the participant have to control, the number and type of clearances required over the time and the number/trajectory of other interfering flights. Subjects have been trained daily for 5 days (SESSIONS T1-T5) and their neurophysiological signals have been recorded in the first (T1), in the third (T3) and in the fifth (T5) session, while the behavioral and performance data have been collected every day. After the training period, the subjects were asked to execute the LABY conditions, in a random order of difficulties, in two consecutive days and after a week since the last experimental session.

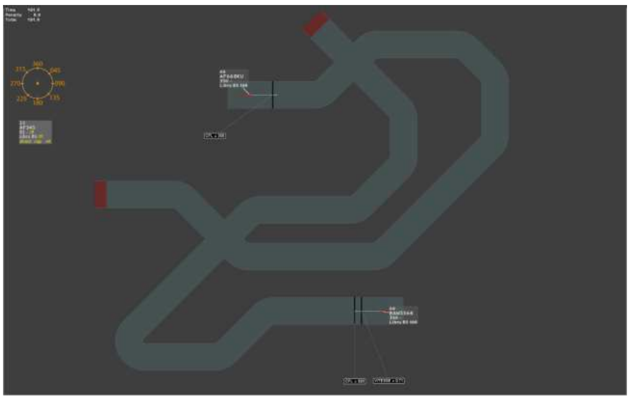

Figure 1. The LABY is a dynamic environment whereby an ATC must issue directional commands to guide *N* airplane(s) around a predetermined route, indicated by a green path, in order to avoid any conflicts or obstacles which may occur during the flight-route.

In this phase of the study protocol, the neuro-physiological signals have been collected in every session, and at the end of each experimental condition the subjects filled the NASA-TLX [15] questionnaire for the evaluation of the perceived workload of the proposed task.

B. Acquisition of the brain activity and of the physiological signals

The Electroencephalogram (EEG) and physiological signals, including vertical electrooculogram (EOG) and electrocardiogram (ECG), have been recorded by the digital monitoring *BEmicro* system (EBNeuro system). The sixteen EEG channels (FPz, F3, Fz, F4, AF3, AF4, C3, Cz, C4, P3, Pz, P4, POz, O1, Oz and O2), the ECG and the EOG channels have been collected simultaneously with a sampling frequency of 256 (Hz). All the EEG electrodes have been referenced to both earlobes, and the impedances of the electrodes were kept below 10 (kΩ). The bipolar electrodes for the heart activity have been placed on the Erb's point, while the bipolar electrodes for the EOG have been positioned vertically on the left eye.

C. EEG analysis

The acquired EEG signals have been digitally band-pass filtered by a 4^{th} order Butterworth filter (low-pass filter cut-off frequency: 30 (Hz), high-pass filter cut-off frequency: 1 (Hz)) and then segmented in epochs of 2 seconds, 0.125 seconds – overlapped. The EOG signal has been used to remove eyes-blink artefacts from the EEG data by using the Gratton and Coles method [16]. The EEG Power Spectral Density (PSD) has then been estimated by using the *Fast Fourier Transform* (FFT) in the EEG frequency bands defined for each subject by the estimation of the *Individual Alpha Frequency* (IAF) value [17]. PSDs in the theta and alpha bands have then been analyzed by estimating the *Coefficient of Determination* (r^2), or *r-square*, between the considered experimental condition and the reference condition. As $0 < r^2 < 1$ by definition, a signed r^2 has been derived by multiplying the coefficient of determination by the sign of the slope of the corresponding linear model of the regression analysis. In this way, it has been possible to obtain information not only about if the two datasets were different, but also about the direction of such difference. A Stepwise Linear Discriminant Analysis [18] has been used to select the most relevant spectral features to discriminate the mental workload levels. In particular, the classifier was trained using data from one triplet (Easy, Medium and Hard) and the extracted parameters were tested over the other remaining triplets within the same session (INTRA cross-validations) or the other sessions (INTER cross validations). Several moving average samples (NMA) have been applied to the output of the classifiers (W_{EEG},): $N_{MA}(1) = 0.125$ (sec), $N_{MA}(8) = 1$ (sec), $N_{MA}(16) = 2$ (sec), $N_{MA}(32) = 4$ (sec), $N_{MA}(64) = 8$ (sec). The moving average was expected to increase the stability and the accuracy of the index with the drawback of introducing delays in the workload estimation, inducing a decrease of the workload refresh rate.

D. ECG and EOG analysis

As well for the EEG, the ECG and the EOG signals have been band - pass filtered, respectively 1-8 (Hz) and 8-16 (Hz), and then segmented in epochs of 8 seconds, 0.125 seconds – overlapped. The HR and the EBR have been estimated by calculating the distance between consecutive peaks occurring in the ECG and in the EOG signals. In particular it have been used the R-peaks and the eyeblinks peaks and then they have been normalized by the z-score transformation with respect to the reference condition, in which the subjects watched the stimuli's tasks without responding to them. As well for the EEG, also for the HR a workload index has been calculated by using a SWLDA at different output rates (W_{HR}): $N_{MA}(1)$ = 0.125 (sec), $N_{MA}(8)$ = 1 (sec), $N_{MA}(16)$ = 2 (sec), $N_{MA}(32)$ = 4 (sec), $N_{MA}(64)$ = 8 (sec)).

E. Fusion workload index

A Fusion workload index has been calculated as a combination of the W_{EEG} and the W_{HR} based workload indexes. In particular, the two classifiers outputs have been synchronized, because their different delays (EEG: 2 (sec) overlapped of 125 (msec); HR: 8 (sec) overlapped of 125 (msec), and then the new score (Fusion based workload index, W_{Fusion}) has been computed as a linear combination of the W_{EEG} and the W_{HR} score (Equation 1).

$$W_{Fusion} = aW_{EEG} + bW_{HR} \tag{1}$$

The coefficients a and b of the linear combination have been estimated for each subject by means of a simple LDA performed considering the EEG and the HR score distributions (W_{EEG} and W_{HR}) calculated over the cross validations for the three different difficulty levels (Figure 2).

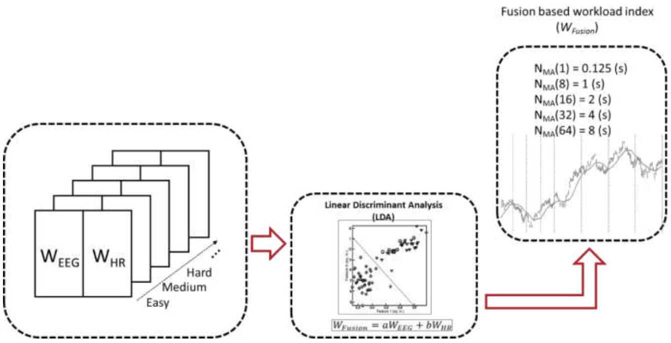

Figure 2. Fusion based workload index assessment (W_{Fusion}). The Fusion workload index (W_{Fusion}) has been calculated as a linear combination of the EEG and the HR based workload indices. The two classifiers outputs were synchronized before the computation of the fusion-based index.

F. Classifier performance analysis

The dataset deriving from the three sessions has been re - organized in 15 triplets (5 triplets per session) of runs (Easy, Medium and Hard). All the possible cross-validations have been considered, training the classifier with one triplet and testing the extracted features over the remaining triplets. The values of the Area Under Curve (AUC) of the Receiver Operating Characteristic [19] describing the accuracy of the system has been calculated from the output of the classifier (for each different refresh rate).

G. Workload score distributions analyses

The workload score distributions of the single subtasks has been calculated using the same approach of the AUC evaluation, thus by training the classifier with each triplet of runs within the sessions and testing the extracted features over all the other triplets. In addition, they have been differentiated two type of cross-validations, in order to investigate how well the classifier performs considering the training and the testing set within the same day (INTRA) and considering the training set from one day and the testing set from another of the other two days (INTER). For summarize, the INTRA type refers to the cross-validations performed considering as training and testing sessions the same day. Contrariwise, the INTER type refers to the cross-validations performed considering as training session one of the three days and as testing sessions those performed in the other two days.

H. NASA-TLX analysis

Subjective perceived workload evaluation was obtained by filling the standard NASA-TLX questionnaire for each subtask (Easy, Medium and Hard). The given subjective scores were used to estimate the perceived workload by considering six different factors: Mental Demand, Physical Demand, Temporal Demand, Frustration, Effort and Performance. The workload scores, ranged from 0 to 100, were obtained for each factor at the end of the questionnaire. The subjective scores of the perceived workload were compared with the workload indices estimated by the online system.

I. Statistical analysis

The results derived from the different methods have been then validated by the statistical analysis performed by using the STATISTICA software (Statsoft). For the Training Protocol, the one-way repeated measures ANOVA (Confidence Interval, CI = .95) was used for all the neurophysiological data with the factor SESSIONS. Such factor has three levels, one for each day of the week in which the EEG recording was made (T1, T3 and T5). For the Workload Protocol, statistical analyses over the i) classifier performances, ii) workload scores distribution and iii) NASA-TLX scores have been performed.

i) A three-way repeated measures ANOVA (CI = .95) has been performed using the classifier (EEG, HR and Fusion based), the couple of subtasks (Easy vs Hard, Easy vs Medium and Medium vs Hard), and the moving average lengths ($N_{MA}(x)$, x={1, 8, 16, 32, 64}) as factors and the related AUC values as dependent variable, for all the subjects and cross-validations. In addition, a Duncan post-hoc test has been performed in order to test the effects between all the factors.

ii) Three two-way repeated measures ANOVA (CI = .95) have been performed, one for each classifier (EEG, HR and Fusion based), using subtask (Easy, Medium and Hard) and Cross-validation type (INTRA and INTER) for each subject as factors and the related workload index distributions (W_{EEG}, W_{HR} and W_{Fusion}) as dependent variables, for all the subjects.

A one-way ANOVA (CI=.95) was performed on the NASA-TLX scores with the subtask (Easy, Medium and Hard) as an independent variable. In addition, Duncan post-hoc tests have been performed in order to test the effects between all the factors

III. RESULTS

A. Training improvement assessment

Throughout the training sessions, the performance of the subjects increased continuously in terms of mean performance level and accuracy. Figure 3 shows the performance's index adopted across the different training days. By the inspection of Fig. 3 it is easy to note the simultaneous increase of the performances level and the decrease of the amplitude of the standard deviations in the learning curve. On the second day of training, all the subjects reached at a good level of performance (almost the 90%) and since the third day, they could reach performance level higher than 95%. The one-way ANOVA performed on the global LABY score showed significant differences across the sessions ($F(4, 180) = 34.74$ with a $p < 10^{-5}$). The post-hoc Duncan test showed that the first two sessions (T1 and T2) were statistically different from all the others ($p < 10^{-4}$) while the last three ones (T3, T4 and T5) were not statistically different to each other.

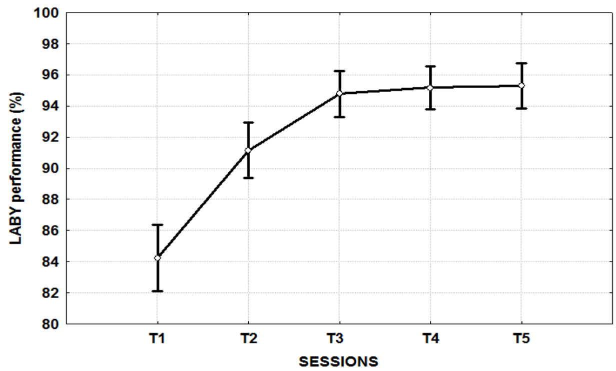

Figure 3. The trend of the global LABY score across the five different training sessions (T1÷T5). The figure reports the mean performance value and the standard deviations for the sessions. A statistical significant increase of the performance was obtained at the end of the period when compared to the first day of training.

The ANOVA results reported in Figure 4 show a statistical significant modulation of the of EEG PSD in theta band over the frontal areas (EEG channels: AF3, AF4, F3, Fz, and F4) across the different training sessions ($F(2, 400) = 43.45$), $p < 10^{-5}$ and also the Duncan's post-hoc test confirmed these differences $p < 10^{-4}$. It is evident that in the central session (T3), when the subjects have been supposed to have learnt how to execute correctly the task and focused the cognitive resources for improve their performances, the frontal PSD theta reached the highest increment respect all the other sessions.

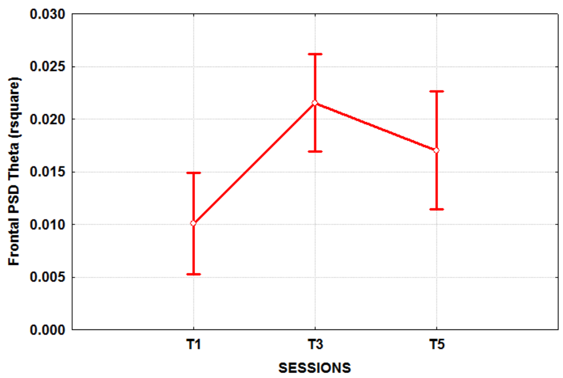

Figure 4. Mean EEG PSD (r-square) in theta band over the frontal EEG channels AF3, AF4, F3, Fz and F4 across the training sessions T1, T3 and T5. At T3, the frontal PSD theta reached the highest increment ($p < 10^{-5}$).

Figure. 5 shows the trend of the parietal EEG PSD in alpha band over the EEG channels P3, Pz and P4, represented as variation of signed r-square. Repeated measures ANOVA showed significant differences of the parietal PSD alpha ($F(2, 240)=43.27$ with an associated p value $< 10^{-5}$) and a decreasing trend of the spectral PSD from T1 to T5 has been found out across the training sessions.

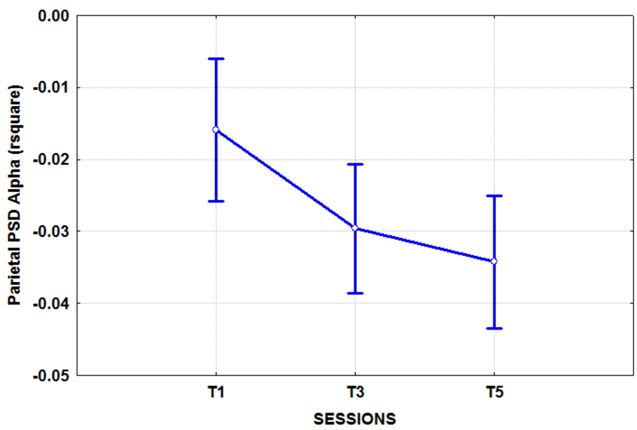

Figure 5. Parietal EEG PSD in alpha frequency band during the training period. The graph reports the signed r-square values estimated in the training sessions (T1, T3 and T5). The continuous decrement of the parietal PSD alpha is significant across all the training sessions ($p<10^{-5}$).

Figure 6 and 7 show the results of the statistical analysis of the autonomic parameters of HR and of EBR. The HR shows that the subjects were emotively engaged in correspondence of the central training session (T3), as the HR in T3 was the highest one, and that at the end of the training period they were more confident with the experimental task, as both the HR and the EBR decreased and increased, respectively. In fact, the Duncan's post-hoc tests reported significant ($p<.01$) differences between the HR and EBR values of the first (T1) and last (T5) training session. In addition, the EBR z-score shows how the subjects kept to pay attention to the task, as it was negative even at the end of the training.

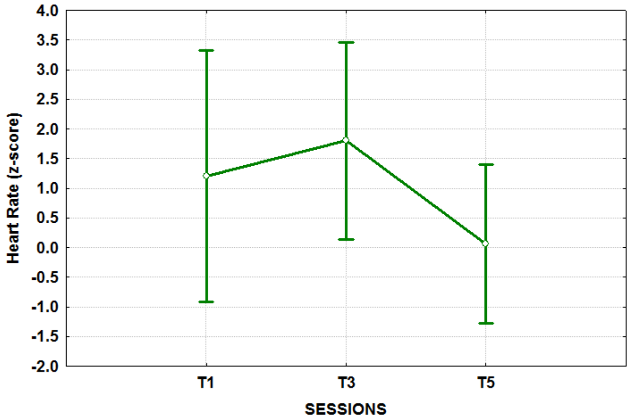

Figure 6. Heart Rate (z-score) values across the trianing sessions. The trend shows how in the central part of the training period (T3) the subjects showed an high emotive engagment, as the HR got the highest value.

The one-way ANOVA for the NASA-TLX data (Figure 8) shows significant differences among the training sessions ($F(4, 180)=19.39$ and $p< 10^{-5}$). A post-hoc test allowed to check out that the average scores of the NASA-TLX were statistically different until the fourth session (T4), whereas the T4 and T5 sessions were perceived as similar in terms of workload.

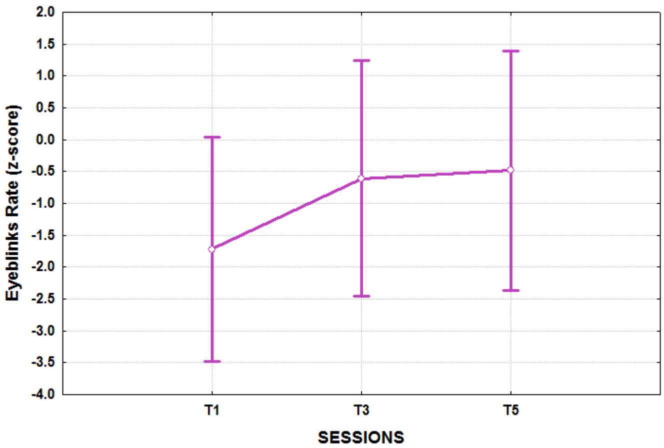

Figure 7. Eyesblink rate (z-score) values across the training sessions. The values are all negative because the subjects paid attention to the task for the whole training period and it shows how the subjects got more confident with task session after session.

B. Workload evaluation and classification

The ANOVA analyses (Figure 9) revealed no main effect of the classifiers ($F(2, 135)=.63$, $p=.53$), a main effect of conditions ($F(2, 135)=56.05$, $p=10^{-5}$) and a main effect of refresh time ($F(4, 135)=4.61$, $p=0.0016$). The post-hoc test showed that AUC values calculated using all the three classifiers in the “Medium vs Hard” couple were significantly lower (all $p<10^{-3}$) than the other two ones. In addition, increasing the refresh rate, the AUCs of the system significantly increase (all $p<.05$) only for the EEG based classifier, but not for the other ones.

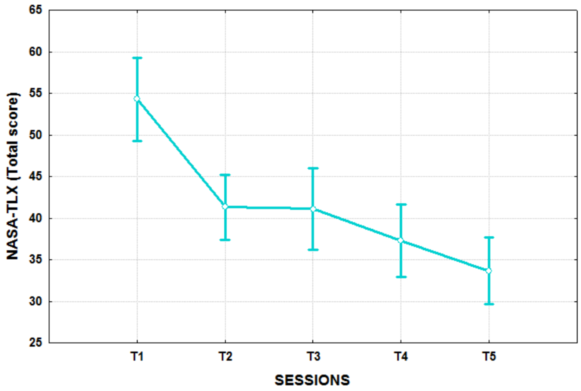

Figure 8. Average NASA – TLX scores of the training sessions. After each training session the subjects perceived the difficulty of the experimental task easier than the previous one.

The fusion based classifier shows higher AUC values of the EEG based classifier at short refresh times (0.125s), and higher AUC values of the HR classifier at long refresh times (8s). Anyhow, these trends are not significant, and this behavior could be associated at the low number of subjects involved in the study (Figure 10).

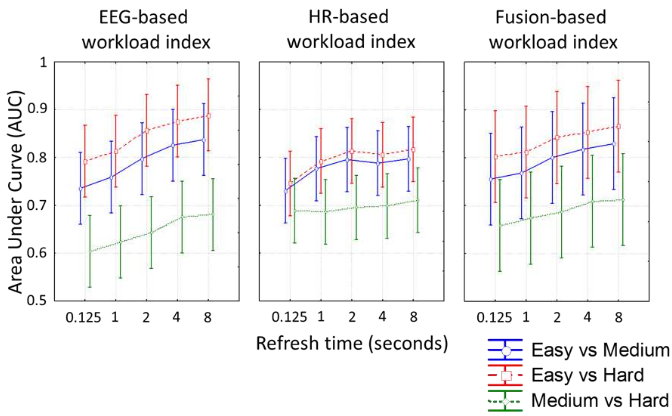

Figure 9. Mean values and related standard errors (CI = .95) of the AUC values achieved using the different classifiers (EEG, HR and Fusion-based) for each refresh time value.

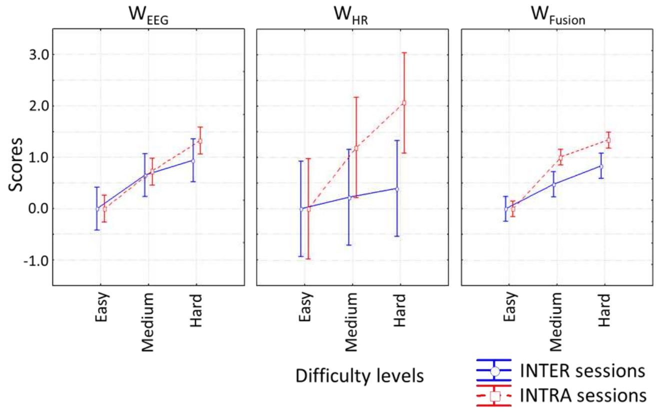

Figure 10. Mean values and related standard errors (CI = .95) of the distributions of the workload indices (W_{EEG}, W_{HR} and W_{Fusion}) evaluated by the three classifier (EEG, HR and Fusion based).

The repeated-measures ANOVA revealed a main effect of the difficulty levels ($F(1,118)=34.60$, $p=10^{-4}$). Subjective perceived workload shows an increasing in the perceived workload as the difficulty of the task increase. This result is consistent with the score distribution analyses, showing a high reliability of the estimated index.

IV. Discussion

The neurophysiological signals, the task performance scores and the experienced workload describe a story in which the subjects could find their own strategies and then got confident with the execution of the proposed LABY task. At the central part of the training period (T3) the cognitive and emotive engagement were the highest, as the frontal PSD theta and the HR got the highest values. The trends of the parietal PSD alpha and of the EBR showed how the subjects kept to pay attention to the execution of the task. In fact, the parietal PSD alpha and the EBR carried on decreasing and increasing, respectively, until the last training session (T5). From a perception point of view, the NASA-TLX scores demonstrated that the subjects experienced less workload, session after session, especially at the end of the training period respect to the beginning of it. Once subjects became confident with the Laby task, it has been tested an algorithm able to estimate in real-time the mental workload of the user, by using the combination of EEG and ECG signals. It has been demonstrated that the combination of these signal allows to differentiate significantly the workload level over three different difficulty level tasks, showing a high discrimination accuracy (AUC > .7). Finally, the calculated workload index showed the same trend of the NASA-TLX workload assessment. The evaluation of the mental workload by using the information derived by biosignals, allows to have a factual measure to triangulate with subjective methods, such as the NASA-TLX. A distinctive advantage with respect to the subjective measurements is the assessment of the variations of the workload within the same task, e.g. each 125 msec. The system allows to evaluate the workload in real-time.

V. Conclusions

Two protocols have been presented in this document, the training and the workload evaluation of ATCOs by means of neurophysiological signals. The integration of information derived by the brain activity, through the EEG, and the physiological signals of ECG and of EOG with the supervision of Experts could be used as possible innovative “cognitive metric” for evaluating the degree of the learning process and the training progress of learners, throughout their periods of professional formation. Also, this method could be applied when the comparison between subjects is required. In fact, after a fixed period of training it could be possible i) to quantify how well the subjects can complete a task, in terms of cognitive resources necessary to the correct execution, and ii) to compare subject’s cognitive performances by estimating the neuro-physiological EEG, HR and EBR parameters presented in this study. In addition, an algorithm able to estimate the mental workload of an operator by using the combination of EEG rhythms and HR signals has been proposed. It has been demonstrated that i) the system is able to significantly differentiate three workload levels related to the three difficulty level tasks employed with a high reliability; ii) the subjective features used for the evaluation of the mental workload remain stable over one week only by using the EEG-based classifier. The combination between the information derived from the EEG and the HR signals allow increasing the performance of the system. Anyhow, this trend is not significant, because of the low sample size. Finally, the subjective evaluation of the workload shows the same trend of the physiological workload indexes (W_{EEG}, W_{HR}, W_{Fusion}).

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