Formal Detection of Attentional Tunneling in Human Operator–Automation Interactions

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Abstract—The allocation of visual attention is a key factor for the humans when operating complex systems under time pressure with multiple information sources. In some situations, attentional tunneling is likely to appear and leads to excessive focus and poor decision making. In this study, we propose a formal approach to detect the occurrence of such an attentional impairment that is based on machine learning techniques. An experiment was conducted to provoke attentional tunneling during which psycho-physiological and oculomotor data from 23 participants were collected. Data from 18 participants were used to train an adaptive neuro-fuzzy inference system (ANFIS). From a machine learning point of view, the classification performance of the trained ANFIS proved the validity of this approach. Furthermore, the resulting classification rules were consistent with the attentional tunneling literature. Finally, the classifier was robust to detect attentional tunneling when performing over test data from four participants.

Index Terms—Attentional tunneling, cognitive state inference, fuzzy neural networks, human factors, human–robot interaction.

I. INTRODUCTION

FOCUSING one's attention on a single item without being disturbed by other environmental stimuli is an essential human mechanism of information processing. However, there is a tradeoff between attention focus and the ability to process other events. The operators' attention allocation is a crucial safety issue in many domains such as the automotive industry [1] and aeronautics [2]. Indeed, the inability for a human operator to detect unexpected changes in the environment may lead the operator to neglect crucial cues (e.g., alarms). Different terminologies have been put forward to describe this phenomenon [1], [3]–[5], but attentional tunneling is one of the most commonly used in human factors. This concept is defined as "the allocation of attention to a particular channel of information, diagnostic hypothesis or task goal, for a duration that is longer than optimal, given the expected cost of neglecting events on other channels, failing to consider other hypotheses, or failing to perform other

tasks [6]." Thus, such an attentional impairment presents interface designers with a paradox: How can one expect to "cure" human operators from attentional tunneling if the alarms or systems designed to warn them are neglected by the operators themselves? Indeed, as different authors postulate, providing information from additional warning systems could worsen the situation as increasing the visual load may induce narrowing of the visual field [3], [7]. Therefore, rather than adding new alarms, a more useful solution would be to use cognitive countermeasures [8]–[10]. These countermeasures are derived from a neuroergonomics approach to cope with cognitive biases [11] and are based on the temporary removal of information on which the human operator is focusing. The overfocused information is replaced by an explicit visual stimulus that is designed to change the attentional focus. Adaptive systems [12] are an interesting avenue to support this strategy as such systems aim to infer the human operator's cognitive and emotional state from different measurement techniques in order to adapt the nature of the interaction and overcome cognitive bottlenecks [13]. In this context, this research provides objective metrics to characterize attentional tunneling and a formal method for countermeasures that could be used to trigger an adequate adaptation from the system.

A. Metrics of Attentional Tunneling

Considering Wickens' definition of attentional tunneling [6], a straightforward way to identify this phenomenon is noting when operators omit unexpected events (e.g., they do not react to alarms) and persevere in their current action pattern. Such an expert approach requires analysis of the operators' behaviors to infer their attentional state (e.g., actions on the user interface reaction time). A complementary approach is to derive attentional tunneling from the measurement of physiological signals and ocular activity. Indeed, this attentional impairment is associated with psychological stress [14]–[16]. Several authors have demonstrated that attentional tunneling results in fewer scanned areas of interest (AOI) on the user interface [6], a decreased saccadic activity [17], long eye fixations [18], and the absence of ocular fixations on relevant cues [2].

B. Formal Inference Techniques

The efficiency of attention tunneling identification depends not only on the selection of accurate metrics but also on the type of classification technique. Moreover, classifying attentional tunneling states on the basis of physiological and behavioral metrics requires some flexibility. Physiological metrics are generally continuous and noisy and there are no mathematical

models of the links between physiology and attention. Only expert models are generally used to link physiology and attention.

Fuzzy logic is an inference technique that is well suited for continuous and noisy inputs [19]. Following a similar approach proposed by Mandryk and Atkins [20], Pizziol *et al.* [21] developed a mathematical model using fuzzy rules to link psychophysiological inputs (e.g., the heart rate (HR) used as a psychological stress indicator) and an attentional output (e.g., "the level" of attentional tunneling). Although this study provided promising results showing the interest of fuzzy logic for such modelling, there was a limitation to this approach. Indeed, the fuzzy rules that link these inputs and outputs had to be set *a priori* from expertise.

A consistent method to avoid such drawbacks is to use automated machine-learning techniques [22], as they allow mathematical links between inputs and outputs to be established from a statistically sound point of view, rather than relying on experts. The machine-learning literature provides a wide range of methods and algorithms to learn efficient classifiers (e.g., neural networks [12], support vector machines (SVMs) [23], hidden Markov models [24]) from which one can find the appropriate method for the specific application. Neuro-fuzzy learning [25] is well suited in this particular case as in addition to its learning ability, the method retains the advantages of fuzzy logic. Furthermore, under certain conditions [26], the fuzzy rules underlying the behavior of the generated classifier can be translated into natural language [27], thus allowing an easier interpretation by researchers.

C. Present Study

The main objective of this research is to provide a formal method using machine-learning inference techniques to detect attentional tunneling from the analysis of psycho-physiological and oculomotor responses that are collected during an experiment [9]. This experiment was designed to provoke attentional tunneling. Participants were asked to perform a task of manually controlling a robot while performing target identification. During the task, a low battery failure was triggered, forcing a safety procedure that required the robot to return autonomously to the base. At this stage, the participants were supposed to stop operating the robot and allow it to return back to the base. The participants were separated in two groups: the control group, whose members did not receive any cognitive countermeasures to help them notice the battery failure, and the countermeasure group, whose members were assisted with a cognitive countermeasure.

In this experiment, the battery failure was used as a probe to determine whether the participants faced attentional tunneling or not, in accordance to Wickens' definition [6]. This approach allowed labeling of attentional tunneling periods for supervised machine-learning purposes. Three attentional tunneling metrics were employed in this study: the HR, the number of AOI (NBAOI) glanced at on the user interface, and the switching rate (SWR). The literature suggests that HR increases with psychological stress [28]–[34], and NBAOI and SWR decrease with attentional tunneling [17], [18]. The calculation of the
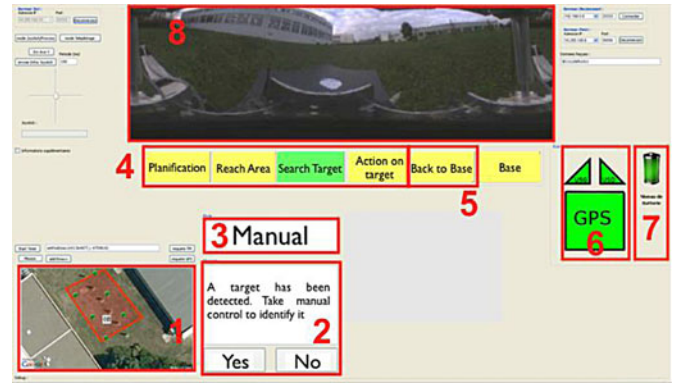

Fig. 1. Ground Station Interface: 1) "tactical map," 2) "interactive panel," 3) "mode annunciator," 4) "synoptic," 5) "back to base," 6) "GPS and ultrasound status," 7) "battery status," 8) "panoramic video."

attentional tunneling periods and the changes in the three associated metrics are presented in Section III.

These three metrics were used to train an adaptive-network-based fuzzy inference system (ANFIS) to infer attentional tunneling according to the labeling that is used in the experiment. The ANFIS was chosen as it combines the expressive power of fuzzy representations with the adaptability of neural networks for more accurate predictions. The performance of this inference system was assessed in terms of learning and robustness. A support vector machine was implemented to compare classification performances of these two algorithms. The methodology to train the ANFIS and the performance analysis on the robotic experiment is described in Section IV.

II. EXPERIMENTAL METHODS

A. Material

The experimental setup consisted of a robot that is equipped with different sensors and a ground station that is used to control the robot. The robot can be operated in the "manual" or "supervised" mode. In the manual mode, the robot was controlled by the operator with a joystick. In the supervised mode, the robot performed waypoint navigation autonomously, but any action of the operator with the joystick allowed him/her to take over until the joystick was released. The ground station (see Fig. 1) used a 24-in display that provided information for control and supervision of the robot. The operator could not see the robot and only gathered information regarding the scenario through the display interface

B. Experimental Scenario

The experimental scenario was designed to induce attentional tunneling. The scenario consisted of a target localization and identification task. The target was a black-metal panel with red stripes and two messages written in white: "OK," (front side) "KO" (backside). The mission was 4 min long and composed of four main segments: S1—"Reach the area," S2—"Scan for target," S3—"Identify target," and S4—"Battery Failure."

At the beginning of the mission, the operator navigated the robot in the supervised mode to reach the search area (S1).

Upon arrival, the robot began detecting the target (S2). When the robot was within the vicinity of the target, the operator was notified to control the robot in the manual mode for identification and differentiation of both messages (S3). The use of a panoramic video [35] and the introduction of a 1-s lag in the control loop [36] increased the task difficulty and favored excessive focus. While the operator was involved in the identification task (S3), a "low-battery event" was sent by the experimenter (S4). This event triggered a safety procedure that forced the robot to automatically return to base in the supervised mode unless the operator overrode this procedure with a command from the joystick.

As this failure happened at a crucial moment in the mission when the operator was particularly committed to handling the robot near the target, it was expected that the operator would not notice the alerts on the interface warning of the "low-battery" event and would persist in achieving the target detection task. Thus, the operator would experience attentional tunneling.

C. Participants

Twenty-three participants (all males but four females, mean age = 29.52, SD = 9.14), all French defense staff from Institut Supérieur de l'Aéronautique and de l'Espace and The French Aerospace Lab were recruited by local flyers and emails. Informed consent was received at the start of the experiment. Participants were randomly assigned to two independent groups.

1) The control group consisted of 12 participants (all males but two females, mean age = 28.25, SD = 6.64). No countermeasure was provided to help them detect the battery failure.
2) The countermeasure group consisted of 11 participants (all males but two females, mean age = 30.90, SD = 11.45). A countermeasure was provided to help them detect the battery failure.

D. Procedure

The participants sat 1 m from the user interface in a closed room with no visual contact with the outdoor playground where the robot moved. A ProComp Infinity system (Thought Technology) electrocardiogram was applied to the participants' chests using Uni-Gel to enhance the quality of the heart beat signal. A Pertech head-mounted eye-tracker was placed on their heads to observe their oculomotor behaviors. Participants rested for 3 min to establish a physiological baseline and performed a 13-point eye-tracking exercise to calibrate both sensors.

A briefing was provided on the mission, the user interface, and the two guidance modes. Participants were trained for 20 min on controlling the robot through the panoramic video screen with the two guidance modes. They were told that four incidents (low-battery event, communication breakdown, GPS loss, and ultrasound sensors loss) might occur during the mission. However, only the low-battery event occurred during the experiment. The associated procedures and the expected robot behaviors were explained for each of these incidents. During the low-battery event, participants were to "release immediately the joystick and let the robot go back to base"; during the com-
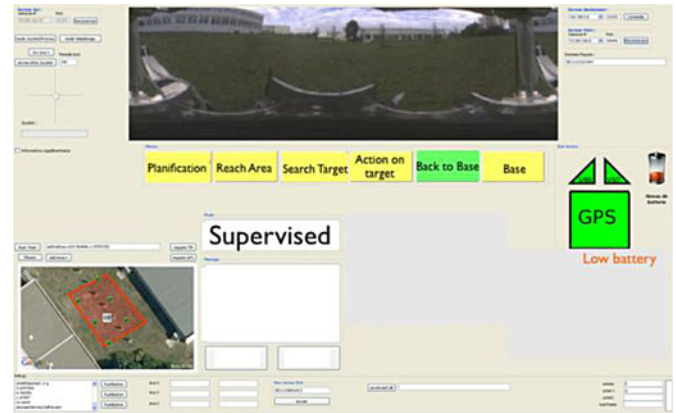

Fig. 2.   Interface as the battery failure alarm is triggered.

munication breakdown and the GPS failure, they were to "wait for the communication or the GPS signal to return"; and during the ultrasound sensor failure, they were to "use the joystick to avoid obstacles."

The participants were also trained on how to diagnose these four issues from the user interface. The low-battery event caused three main changes in the user interface (see Fig. 2): the battery icon turns to orange with an associated "low battery" message (see Fig. 1, area 7), the mode changes from manual to supervised and flashes twice (see Fig. 1, area 3), and the segment status becomes back to base (see Fig. 1, areas 4 and 5). There was only one change each for the other scenarios—communication breakdown: "the panoramic video is frozen"; GPS loss: "the GPS icon becomes red and the mode changes to manual"; ultrasound sensor failure: "the ultrasound icons turn to red." After the training session, there was a short test to verify participants' understanding of the instructions and procedures. The experimental scenario that involved the battery failure was initiated and only occurred in one trial per participant.

E. Failure and Cognitive Countermeasure

As described in Section II-B, the low-battery event triggered an automatic procedure that forced the robot to return to the base by the shortest route. The participants were informed of the occurrence of this event through the user interface as described in Section II-D.

A cognitive countermeasure was designed to help the participants of the countermeasure group to deal with attentional tunneling. It was hypothesized that the operators would be excessively focused on the panoramic video window for target identification (see Fig. 1, area 8). This window was removed for 1 s, replaced by the explanation of the robot behavior for 3 s, and reappeared with the explanation superimposed for three more seconds. Finally, the interface returned to its nominal state. The robot did not move while the cognitive countermeasure was sent to the operator.

F. Metrics Computation

1) Heart Rate: The electrocardiograph was sampled at 2048 Hz. The BioGraph Infiniti software was used to export

the HR computed from the interbeat-interval (R–R interval) every second of the experiment. No complementary spectral analysis methods were used because of the length of the time window required to process this kind of analysis (at least 4 to 5 min [33]): only a moving average filter of 5 s was applied to smooth the HR signal. Because of a commonly observed difference in HR baseline values among participants, HR values were standardized: For each participant, the mean HR of the resting period was subtracted from the HR data [37]. Therefore, the relevant metrics was the difference between the current HR and the baseline, expressed in beats per minute.

2) Number of Areas of Interest: The EyeTechLab eye tracking software provided timestamped data of the cartesiancoordinates of the participants' eye gazes on the visual scene at a 25-Hz sampling rate (40 ms between samples). Eight AOI were defined on the user interface as presented in Fig. 1, identified by red rectangles. Each eye position was labeled in accordance to the most relevant AOI; if the eye position was not in an AOI perimeter it was labeled as "AOI number 0." The NBAOI was computed every second of the experiment. Each value of NBAOI was the number of AOIs used during the last 20 s.

3) Switching Rate: Similarly to NBAOI, SWR relied on the eye tracking data. SWR was also computed every second, and corresponded to the number of gaze transitions from one AOI to another during the last 10.5 s, expressed in number of transitions per minute. Pizzol *et al.* [21] provide a more precise definition of NBAOI and SWR.

4) Data Collection: The raw measurements that constitute the three metrics were collected with no online processing. The metrics were computed offline and synchronized. For each participant, the final data were stored in a timestamped log as a sequence of triplets (HR, NBAOI, and SWR), with each triplet covering 1 s of experiment. Two examples of metrics recordings can be found on Figs. 9 and 10.

III. EXPERIMENTAL RESULTS

A. Behavioral Results and Expert Labeling of the Periods of Attentional Tunneling (TUN)

The results of the control group revealed that eight participants out of 12 (66.67%) experienced attentional tunneling: They persisted in examining the target instead of letting the robot go back to base. Although they felt surprised by the behavior of the robot, these participants all declared that they neither noticed the low-battery event nor the other changes on the user interface. The other four participants reported that they had noticed the failure and had decided to let the robot go back to base. These subjective results were consistent with the oculomotor measurement that revealed that these four participants glanced at the battery icon prior to releasing the joystick. These participants achieved the appropriate situation awareness with no help and conducted the mission successfully.

In contrast, all 11 participants from the countermeasure group noticed the battery failure and understood the behavior of the robot. The eye-tracking analysis showed that all of the participants who gazed at the alarm released the joystick to let the robot go back to base. In this group, 10 out of 11 participants

made the decision to stop the mission and let the robot go back to base in the supervised mode. Only one deliberately persisted in identifying the target for 50 s until the battery failed and therefore did not achieve the mission. That participant believed that the remaining power was enough to finish the mission despite the occurrence of the battery failure. His data were not used in this study.

There is no straightforward method to measure the level of attentional tunneling. However, thanks to an expert approach as described in Section I-A, small periods could be labeled with an attentional tunneling level (TUN) of 1 or 0 during the last segment of the experiment (S4). Indeed, according to Wickens' definition, the detection of the unexpected battery failure event was used as an attentional tunneling probe [6] which led to two types of labels:

1) *TUN = 1*: Eight samples were labeled with TUN = 1 from the failure until the end of the experiment. They correspond to the eight participants from the control group who did not glance at the battery failure icon and persisted in examining the target instead of letting the robot go back to base. These samples were used to train the ANFIS.

2) *TUN = 0*: Ten samples were labeled with TUN = 0 from 20 s after the failure until the end of the experiment. They correspond to the ten participants from the countermeasure group, who noticed the failure immediately and followed the associated procedure (let the robot go back to base in supervised mode). Discarding the first 20 s nullifies noise because of the cardiac response latency [38] after the failure. These samples were used to train the ANFIS.

3) *TUN = 1/0*: Four participants were labeled with TUN = 1 until they glanced at any of the following: the mode annunciator (AOI3), the synopsis (AOI4), the "back to base" sign (AOI5), and the battery status (AOI7). They were labeled with TUN = 0 afterward until the end of the experiment. They correspond to the four participants from the control group who reported that they had noticed the failure and had decided to let the robot go back to base. These data were used neither for the inferential analysis nor for the training of the ANFIS but only to test the model.

B. Inferential Analysis of the Input Raw Data

The approach thus far has consisted of definingthe three different physiological and oculomotor metrics (HR, NBAOI, and SWR) that characterize the psycho-physiological evolution of each participant along the experiment. Parametric repeated-measures ANOVA and Fisher's least significant difference test were used to examine the effects of the mission segment type on the three metrics. A categorical explanatory variable was used in the analysis to check for differences between the two categories of participants depicted previously, TUN = 0 ($n = 10$) and TUN = 1 ($n = 8$). The four participants from the TUN = 1/0 group were not included in the analysis. All tests were conducted at $\alpha = 0.05$.

1) *Heart rate (see Fig. 3):* The two-way repeated-measures ANOVA showed a significant group $\times$ segment type interaction, $F(3, 48) = 13.60$, $p < 0.001$, $\eta^2_p = 0.46$ on HR.
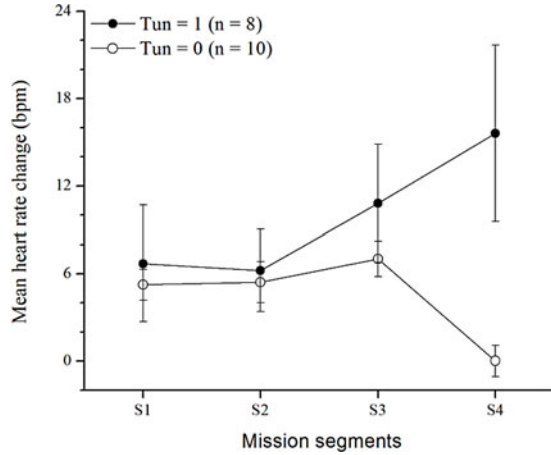
Fig. 3.   Mean heart rate changes across the four mission segments for each category of participants. Error bars represent the standard error of the mean.
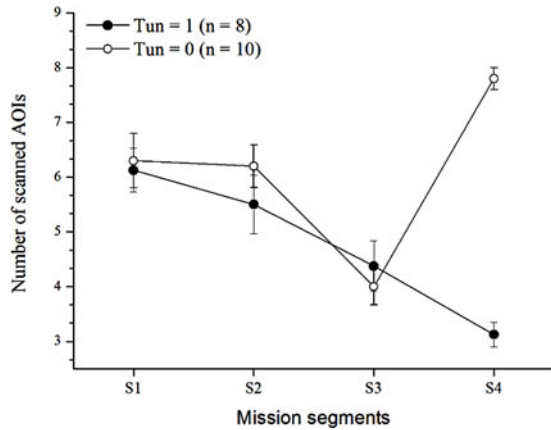

Fig. 4.   Mean number of scanned AOI according to the four segments for each category of participants. Error bars represent the standard error of the mean.

Paired comparisons indicated that the mean HR change differed between the TUN $= 0$ and the TUN $= 1$ groups during S4 ($p = 0.001$), which is the segment containing the battery failure. HR significantly declined between S3 and S4 in the TUN $= 0$ group ($p < 0.001$); on the contrary, it significantly increased between S3 and S4 in the TUN $= 1$ group ($p = 0.018$).

2) *Number of scanned AOIs (see Fig. 4):* There was a significant group $\times$ segment type interaction, $F(3, 48) = 21.35$, $p < 0.001$, $\eta^2{}_p = 0.57$ on NBAOI. Paired comparisons showed that the number of scanned AOIs differed between the TUN $= 0$ and the TUN $= 1$ groups during S4 ($p < 0.001$). Paired comparisons revealed that the NBAOI significantly increased from S3 to S4 in the TUN $= 0$ group ($p < 0.001$), whereasthis value dropped in the TUN $= 1$ group ($p = 0.021$).

3) *Switching rate* (see Fig. 5): The same analysis performed on the gaze SWR (gaze transitions from AOI to AOI per minute) also revealed a group $\times$ segment type interaction, $F(3, 48) = 16.98$, $p < 0.001$, $\eta^2{}_p = 0.51$) on SWR. During S4, the transition rate differed between the TUN $= 0$ and the TUN $= 1$ groups ($p < 0.001$). In the latter segment, the
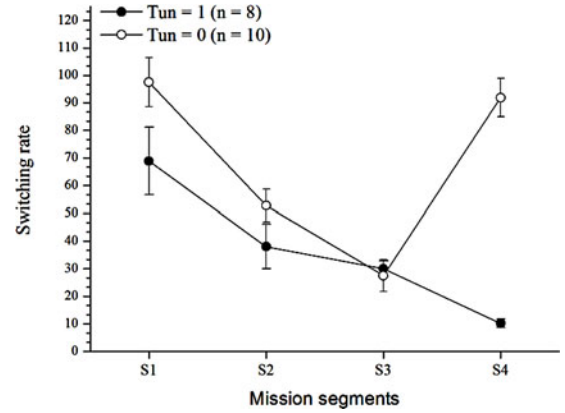

Fig. 5.   Gaze SWR according to the four segments for each category of participants. Error bars represent the standard error of the mean.

mean transition rate increased drastically in the TUN $= 0$ group ($p < 0.001$), whereas it decreased in the TUN $= 1$ group ($p = 0.038$).

These results are consistent with the previous literature on attentional tunneling. Participants from the TUN $= 1$ group were highly focused on the demanding identification task during S4 as revealed by the decrease of the NBAOI and SWR. Their inability to successfully perform this critical task generated stress [39], associated with the higher HR during S4 [28]–[34]. Conversely, participants from the TUN $= 0$ group did not faced such stress. Their HR was relatively lower during S4. One has to consider that these participants noticed the alarm and just let the robot go back to base autonomously as stated by the procedure. Consistently with [6], [17], and [18], NBAOI decreased on S4 for the TUN $= 1$ group (participants facing attentional tunneling consulted less instruments) and raised for the TUN $= 0$ group. In addition, the SWR decreased for the TUN $= 1$ group on S4 (participants facing attentional tunneling had a reduced saccadic activity) as opposed to the TUN $= 0$ group.

IV. ATTENTIONAL TUNNELING DETECTION

This section presents the machine learning method that was most appropriate for this application, ANFIS, and focuses on its implementation and tuning.

Machine learning aims at automatically generalizing abstract concepts from numerical experimental data. In particular, assigning discrete labels to different measurements, given previous examples of correctly labeled measurements, is known as classification within the supervised statistical learning literature [22]. Assessing whether a person is currently facing attentional tunneling, given the current values of the metrics and previous examples, is hence a classification task. The classification task at hand consists in finding a mapping from the triplets $x =$ (HR, NBAOI, and SWR) to a label TUN in $\{0; 1\}$.

A. Adaptive-Network-Based Fuzzy Inference System to Classify Attentional States

An ANFIS classifier is a five-layered neural network using fuzzy membership functions for the activation neurons of the
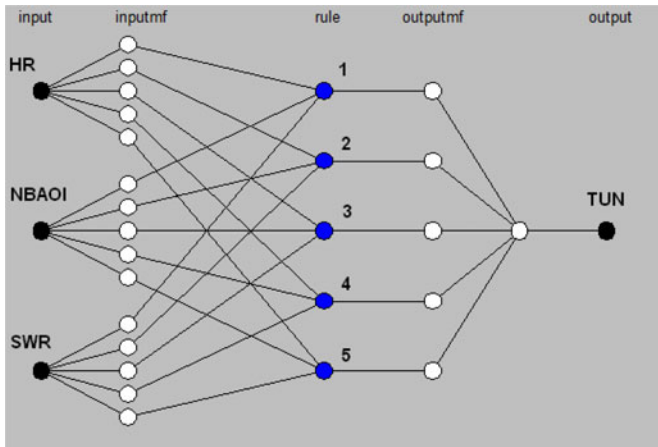
Fig. 6. Example of an adaptive network-based Sugeno-type fuzzy inference system.

Fig. 7. Data distribution between training, checking, and testing datasets.

input layer [hence the name of "fuzzy inference system (FIS)"]. More specifically, as shown in Fig. 6, in the first-order Sugeno fuzzy model [40] that was employed, the following five layers are used.

1) The first layer (see "inputmf" layer in Fig. 6) is a fuzzyfication level where each neuron corresponds to a membership function; it takes the metrics as inputs and outputs the values of the membership functions. The training phase tunes the parameters of these membership functions (e.g., their center position).

2) The second layer introduces nonlinear logical dependences between fuzzified metrics by combining the outputs of the first layer. This combination is done using "and" rules that multiply their inputs together.

3) The third layer takes all output values from the second layer and normalizes them so that they sum to one. In Fig. 6, the second and third layers have been merged into the "rule" layer for clarity. Note that these two layers have no tunable parameters.

4) Then, the fourth layer (see "outputmf" layer in Fig. 6) is a recombination layer between normalized rules that multiplies the output of the third layer by a first-order polynomial of the metrics (hence the name "first-order Sugeno model"). Its neuron parameters are the polynomial coefficients. Note that, for the sake of clarity, the direct connections from the input layer to "outputmf" are not drawn on Fig. 6.

5) Finally, the fifth layer holds a single neuron in which a weighted average of all outputs from the fourth layer results in the ANFIS continuous output value.

The MATLAB fuzzy logic toolbox was used to perform the calculations. As recommended by Jang and Sun [25], the training algorithm used is a hybrid combination of least-squares fitting (for the outputmf parameters) and back propagation gradient descent (for the inputmf parameters). Contrary to a zero-order Sugeno fuzzy model, the output value in a first-order Sugeno is input-dependent because of the first-order polynomial of the metrics. This feature allows for more flexibility in modeling the relationships between the inputs and the output but
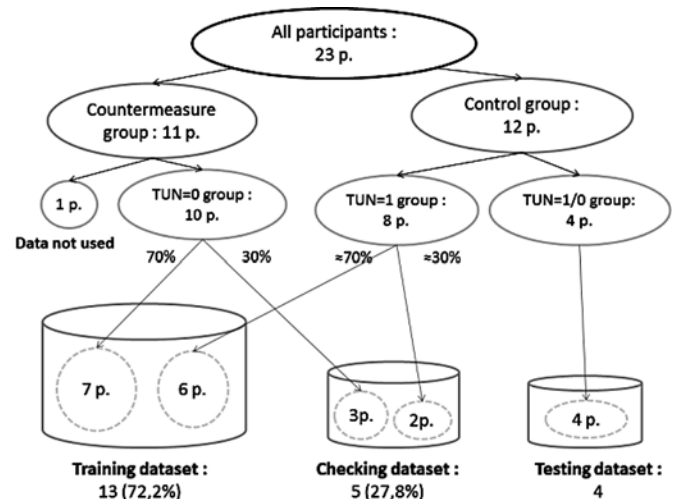
threatens the transparency of the model (i.e., its interpretability) [41], [42].

B. Training Data

ANFIS requires a reference dataset of pairs (x, TUN) where x is the triplet of psycho-physiological parameters (HR, NBAOI, and SWR) and TUN is the level of attentional tunneling. The only appropriate samples are the labeled samples from the segment 4 (cf. Section III-A). Only the samples from the eight participants from the TUN = 1 group and from the ten participants from the TUN = 0 group were used to train the ANFIS and constituted the reference dataset. Cross validation was performed to control the ANFIS training in order to improve its generalization. The reference dataset had to be split in two smaller datasets: the training dataset and the checking dataset. A 70/30% balance was achieved: six out of the eight "TUN = 1" participants and seven out of the ten "TUN = 0" participants were randomly selected and their labeled samples constituted the training dataset (representing 72.2% of the 18 participants). The data from the other two TUN = 1 participants and the three TUN = 0 participants formed the checking dataset (representing 27.8% of the 18 participants). The data from the four remaining participants were used later on to test the ANFIS classifier on new data and evaluate its robustness after the training. They constituted the testing dataset.

A summary of the data distribution is presented in Fig. 7.

C. Parameters of the Fuzzy Inference System

The first step before training the ANFIS is to choose the structure of the FIS itself. This structure depends on the number of inputs and on the number of membership functions for each input. The classical approach at this stage is to use grid partitioning to define the number of membership functions for each input. The subtractive clustering method was used instead in order to let the algorithm discover a statistically sound number of clusters in the training data without biasing it with expert knowledge. The other advantage of this method is that it
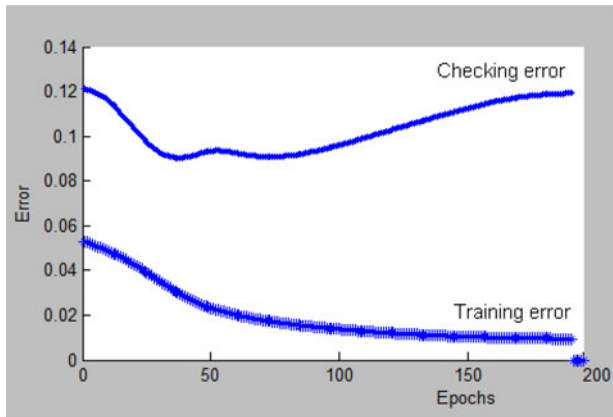
Fig. 8. Error evolution during the training process. The error on the training dataset constantly decreases (bottom curve), while the error on the checking dataset begins to increase after the 38th epoch.

considerably reduces the number of rules that have to be trained by the adaptive neural network, which results in a faster computation and an easier interpretation of the rules after training. Yager and Filev explain in greater detail the mountain clustering method from which subtractive clustering is derived [43]. According to this method,[1] five clusters have been elicited, covering all the samples in the input three-dimensional (3-D) space. Each cluster is a 3-D set, decomposed in one membership function per input dimension. The resulting FIS is therefore composed of five rules corresponding to the five rules to be trained as presented in Fig. 6.

D. Training of the Adaptive-Network-Based Fuzzy Inference System

The training of the ANFIS is possible once the FIS has been set. The tunable parameters of the ANFIS are updated during a repetition of training epochs. Each training epoch is therefore a local optimization of the ANFIS ability to classify the training dataset properly. However, neural networks such as ANFIS are prone to overfitting (because of excessive training epochs, the ANFIS becomes specific in modeling the training dataset, but performs poorly on new data). To avoid this, cross validation was performed: After each training epoch that is based on the training dataset, the ANFIS classified the checking dataset and the classification error was evaluated (checking error). Overfitting appeared after 38 training epochs, as the trained ANFIS did not improve in classifying the checking data despite new training epochs (see Fig. 8). Training is therefore stopped at the 38th epoch. The resulting training error is 2.9% corresponding to the minimum of the checking error (8.9%).

E. Performance on the Training Data

The performance of the ANFIS was evaluated on labeled samples from the segment S4 only, where the ANFIS TUN level prediction can be compared with the expert TUN level.

[1]For the sake of reproducibility, a range of influence of 0.4, a squash factor of 1.25, an accept ratio of 0.5, and a reject ratio of 0.15 were chosen as parameters of the *subclust* MATLAB function.
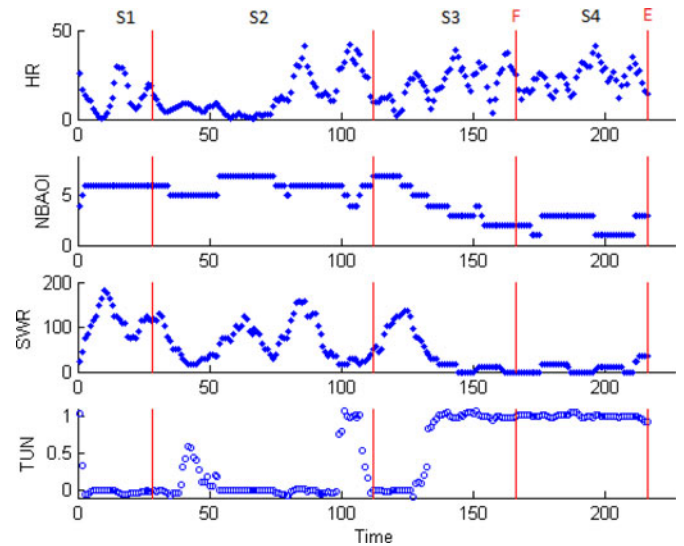

Fig. 9. Evolution of the three metrics for the participant DUPNI (from the TUN = 1 group) during the whole experiment and associated TUN level inferred by the trained ANFIS. F: battery failure time, E: end of the mission.
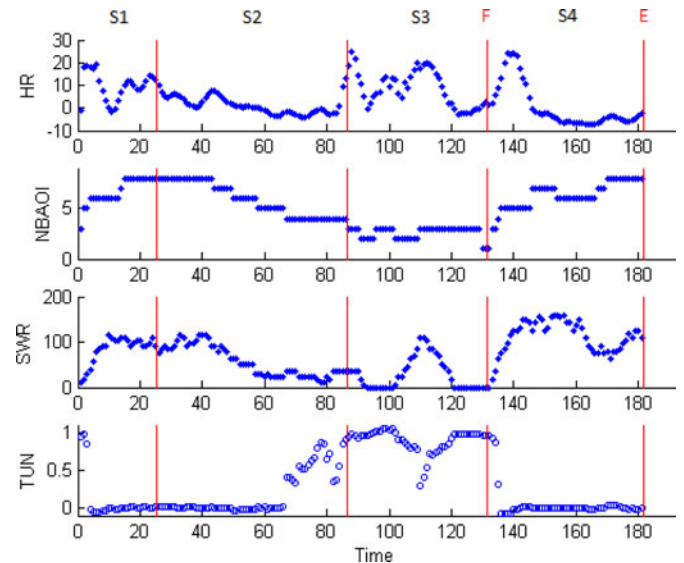

Fig. 10. Evolution of the three metrics for the participant JACRA (from the TUN = 0 group) during the whole experiment and associated TUN level inferred by the trained ANFIS. F: battery failure time, E: end of the mission.

There is a slight dissymmetry in the fitting between training data and the ANFIS prediction. If one separates (TUN = 0) and (TUN = 1) participants within the training set, then the false positive (type II error) rate is 4% and the false negative (type I error) rate is 0%. Two examples of the ANFIS output on the training data can be found in Figs. 9 and 10. The TUN level was computed with the trained ANFIS for the whole mission.

In Fig. 9, the HR rose around the end of S2 and kept a high variability across S3 and S4. NBAOI remained between 5 and 7 before S3, progressively dropped during S3 and remained around 2 till the end of the experiment. SWR also dropped during S3 to reach values close to 0 until the end of the experiment. The TUN level increased during S3 and remained close to 1 until the end of the experiment. These evolutions supported the

TABLE I
CROSS VALIDATION ERROR WITH THE SVM WITH DIFFERENT KERNEL
FUNCTION TYPES

Kernel function Type	Checking error
Linear	1.9 %
Quadratic	2.6 %
Polynomial	3.8 %
Radial Basis Function	2.3 %

expert hypothesis: Participant DUPNI experienced attentional tunneling during the all of S4.

In Fig. 10, HR rose abruptly at the beginning of S3 and S4. NBAOI slowly decreased from values around 8 during S2 to reach its minimum values around 2 during S3 and rose back to values around 7 during S4. SWR follows a similar evolution as NBAOI. These evolutions supported the expert hypothesis: Participant JACRA did not face attentional tunneling during the whole segment 4.

F. Support Vector Machine Comparison

Using the same training and checking datasets, the same classification task was performed with a SVM trained with the Bioinformatics toolbox in MATLAB. Here, the SVM is used as the reference method to compare the results obtained with the ANFIS. For more details about the SVM, see [44]; [45]–[47]. The results of the SVM cross validation, with different kernel function types, are presented in Table I.

The linear kernel performs best in this experiment; therefore, this kernel was employed for the SVM. Comparing and analyzing the checking error differences between the different kernels is beyond the scope of this paper.

In order to compare the predictions of both methods in terms of binary outputs (0 or 1, instead of continuous values), the continuous ANFIS output was rounded to the nearest integer and only the sign of the SVM output was considered. The rounded predictions of the ANFIS have been compared with the expert TUN values on the checking dataset and an error of 1.1% was found. It is a better score than the 1.9% obtained with the linear kernel SVM (see Table I).

Furthermore, the prediction discrepancy between the two classifiers was studied in order to verify whether there was agreement when one was misclassified an example. It appeared that all elements misclassified by the ANFIS were also misclassified by the SVM predictor. Therefore, both methods exhibit consistent behavior. Consequently, for the 1.1% of the checking set misclassified by the ANFIS, one can conjecture that the checking examples are either outliers or exhibit values that are too different from the training set to be classified accurately.

G. Adaptive-Network-Based Fuzzy Inference System Analysis

1) Adaptive-Network-Based Fuzzy Inference System Rules Interpretation: The clusters determined by the subtractive clustering method and a representation of the trained fuzzy rules can be found in Fig. 11.

As mentioned in Section IV-A, contrary to a zero-order Sugeno model, the transparency is not granted with a first-order
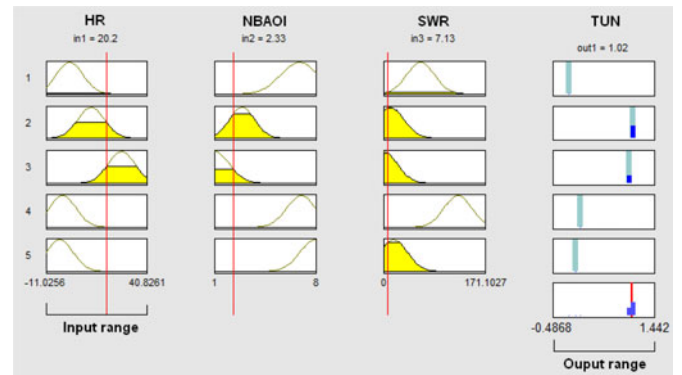

Fig. 11. Clusters and rules representation of the trained ANFIS. The first three columns represent the three inputs. Each column is composed of five lines corresponding to the five clusters elicited by the subtractive clustering algorithm. The Gaussian curves represent the associated membership functions. The yellow levels (between 0 and 1) are the membership function activations depending on the three input values (vertical red lines). The activations of the output rules are computed line by line, depending on the activation of the three input membership functions (a rule is fully activated when the three membership functions are fully activated). The contribution of each output rule is then defuzzified in the right column. Finally, the TUN output is computed via a weighted sum of the five output contributions (vertical red line in the bottom right rectangle).

Fig. 12. Fuzzy domain definition used to translate the ANFIS rules in natural language and associated thresholds in the metrics domains.

Sugeno. It appears that the first-order features in this model are negligible when compared with their constant counterparts (i.e., the first-order polynomial coefficients in the fourth layer are negligible when compared with the zero-order coefficients). Therefore, this model behaves almost like a zero-order Sugeno and preserves its interpretability from a linguistic point of view.

In order to translate the five fuzzy rules in the natural language, seven fuzzy domains were defined from "very low" to "very high" (see Fig. 12). Among the five rules that are trained by the ANFIS, three of them "pull" the TUN output to 0 when they are activated (see rules 1, 4, and 5, Fig. 11). These rules are activated when:

1) (HR is low) and (NBAOI is high) and (SWR is medium low);

TABLE II
CROSS-VALIDATION ERROR COMPARISON BETWEEN THE TWO-INPUT AND THE THREE-INPUT CLASSIFIERS

	Epochs	Training error	Checking error
All 3 inputs	38	2.9 %	8.9 %
Without HR	59	6.5 %	11.8 %
Without SWR	95	7.8 %	15.2 %
Without NBAOI	> 100	9.6 %	21.2 %

2) (HR is low) and (NBAOI is high) and (SWR is medium high);

3) (HR is low) and (NBAOI is very high) and (SWR is low).

The remaining two (rules 2 and 3) that "pull" the output to one are activated when:

1) (HR is medium) and (NBAOI is low) and (SWR is very low);

2) (HR is high) and (NBAOI is very low) and (SWR is very low).

2) Metrics Importance in the Adaptive-Network-Based Fuzzy Inference System Performance: In order to evaluate the role of the three metrics used as inputs in the diagnosis of attentional tunneling, the performance of the previously trained three-input classifier was compared with three classifiers trained with a combination of only two inputs out of three. The same training method was used to train these new classifiers. The number of epochs at which the checking error increased varied from one classifier to another. The results presented in Table II reveal that the three metrics contributed to the attentional tunneling classification as the checking error is minimal when using them together as inputs. NBAOI appeared to be the most important metric among the three as the checking error raises to 21.2% when training the ANFIS without this metric. SWR also played a more important role in predicting attentional tunneling than HR, which appeared to only slightly improve the diagnosis (checking error is 11.8% without HR compared with 8.9% when added as the third input).

H. Adaptive-Network-Based Fuzzy Inference System Testing: Classification Over New Data

In order to check the robustness of the ANFIS classifier, it was tested on the four participants from the TUN = 1/0 group who detected the failure before the end of the experiment, and whose data were used neither for training nor for checking.

Consistently with the expert approach used to label the samples (see Section III-A), we first determined from the data:

1) the level of attentional tunneling at the moment of the failure; and

2) the time when the participants switched from attentional tunneling (TUN = 1) to a nominal behavior (TUN = 0).

The comparison between the latter expert results and the outputs of the ANFIS classifier appears to be consistent as presented in Table III. An example of the inference of the level of attentional tunneling of one of these four participants can be found in Fig. 13.

TABLE III
COMPARISON BETWEEN EXPECTED THE TUN LEVEL AND ANFIS CLASSIFICATION

	Expert	ANFIS
Participants	TUN level at failure	TUN level at failure
	T when Gaze at alarm cues	Time when TUN=0
	T when Release joystick	
PENSE	1	1.026
	18s	17s
	45s	
NIVAL	1	1.019
	20s	27s
	30s	
HOSAL	1	1.03
	20s	22s
	22s	
DASJE	0	-0.02
	0s	0s
	16s	

For example, participant NIVAL was considered as facing attentional tunneling (TUN = 1) at the moment of the failure and remained in that state 20 s. Before he noticed the alarm (expert point of view). The ANFIS classifier output was at TUN = 1.019 at the moment of the failure and abruptly dropped to values close to 0 after 27 s.
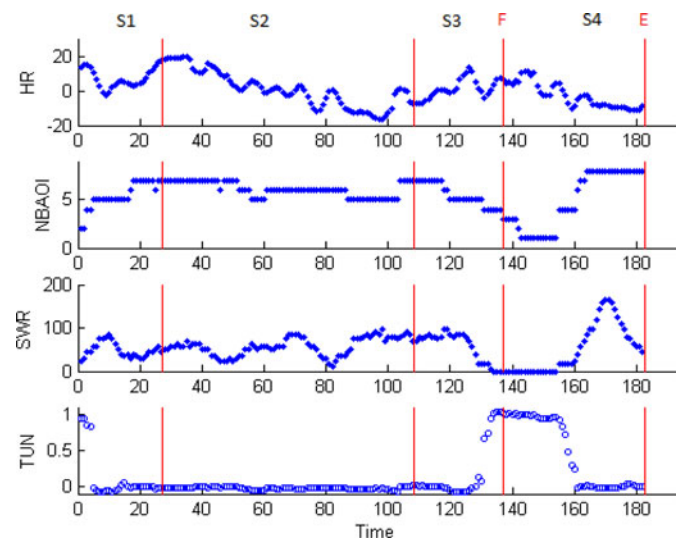

Fig. 13. Evolution of the three metrics for the participant HOSAL from the TUN = 1/0 group and associated TUN level computed by the trained ANFIS. F : battery failure time, E : end of the mission.

V. DISCUSSION

In this paper, the ANFIS method was applied to the detection of attentional tunneling. This formal approach was tested *a posteriori* on data collected during an experiment conducted in the domain of human operator–robot interactions. The training of the algorithm was performed using samples from the last segment of the mission when a failure occurred. The absence of perception of the visual alerts associated with the failure and the persistence of the participants in their initial goal were used as objective indicators of attentional tunneling. The inputs of the ANFIS consisted of a set of three physiological and oculomotor parameters that are known to be associated with attentional tunneling in the human factor literature.

For the machine-learning purpose, the first objective was to ensure that it was possible to collect data from participants who faced attentional tunneling versus participants who did not. The

experiment was successful in generating these two types of behaviors. Indeed, eight participants faced attentional tunneling from the battery failure until the end of the experiment, whereas ten did not during the same segment. These behavioral results were consistent with the psychophysiological and oculomotor measurements. Indeed, during S4 (segment after failure), the group who faced attentional tunneling (TUN = 1) exhibited a higher HR, a lower saccadic activity, and fewer scanned AOI than the group who noticed the alarm (TUN = 0). Furthermore, the inferential analysis on the three metrics showed significant segment type × group interaction that validated the choice of the three metrics to derive attentional tunneling. Indeed, the group who faced attentional tunneling (TUN = 1) had a significantly higher HR, a lower saccadic activity, and fewer scanned AOI on S4 than on S3 even though the task they performed over these two segments was similar. This result highlighted a change in the metrics that was not accounted for a change in the task but that was consistent with the literature showing a raise in attentional tunneling. These results were encouraging for trying to automate the diagnosis of attentional tunneling with a formal machine-learning method as ANFIS.

An objective of this study was to test the efficiency of using ANFIS to identify degraded attentional states. The results on the training dataset show that this approach was appropriate to identify the links between attentional tunneling and the psycho-physiological metrics. Indeed, when using the continuous output, the ANFIS matched the checking dataset with an error of 8.9%. When rounded, the ANFIS output matched the checking dataset with 1.1% error. The performance on this task is better than the performance of the SVM, one of the reference techniques in the machine-learning domain.

The classifier also proved to be robust over new data from the four participants kept for testing and could identify the moment when the participants stopped facing attentional tunneling. This promising result shows that it is possible to train the ANFIS on a restricted set of participants who faced attentional tunneling, and then to use this trained ANFIS as an attentional tunneling inference system. Indeed the rules learned from the training were relevant and could be generalized to diagnose attentional tunneling across new participants.

Another great interest of ANFIS is that it provides objective rules that could be interpreted in terms of natural language. This advantage is particularly relevant for human factor purposes as it allows experts to compare them with known relationships between metrics and cognitive performance. The results of our study revealed that the rules of our classifier were consistent with the literature about attentional tunneling. Indeed, they highlighted that attentional tunneling was related with a strong reduction of the NBAOI and a decrease in the SWR which corresponded respectively to fewer scanned AOI on the user interface and a decreased saccadic activity as proposed by [2], [18]. Furthermore, the HR indicator confirmed that this narrowing of the visual field on specific sources was accompanied with psychological stress as previously demonstrated by [14]–[16]. On top of giving the rules in the natural language, the ANFIS provided numerical thresholds that could be identified while translating the fuzzy domains into the metrics domain.

Furthermore, our results suggested that the contribution of the NBAOI metric is most important to the classification, followed by SWR and finally HR. This order is coherent with the observed effect sizes (η^2_p) in the inferential analysis (group × segment type interaction). The proportion of the variance attributable to each metrics was ordered identically (NBAOI, $\eta^2_p = 0.57$; SWR, $\eta^2_p = 0.51$; HR, $\eta^2_p = 0.46$). From the human factors point of view, it means that the identification of attentional tunneling could not be optimized without the other two metrics (SWR and HR). In other words, an operator who gazes upon a very limited number of AOIs would not be considered as facing attentional tunneling without demonstrating a low SWR between these AOIs and a high HR.

Although the ANFIS classifier performance is promising to detect attentional tunneling, its efficiency remains limited considering domains of applications such as aviation or unmanned vehicles where safety is at stake. Indeed, a challenge of this research is to design real-time algorithms that automatically trigger cognitive countermeasures and a lack of reliability could lead to trigger spurious countermeasures. Such an intervention must be considered as a last resort when the other traditional alerts prove to be inefficient to cure attentional tunneling. Therefore, the first step to refine this approach would be to integrate more metrics such as the blink rate, the vergence, and the pupil size, which are known to be relevant indicators of attentional tunneling [48], [49], [1]. The inclusion of such metrics would improve the accuracy and precision of the classifier, therefore making it a more reliable source of information to trigger an adaptation of the interface. Another way to avoid spurious intervention would be to take the whole context of the system into account, as it could disable the attentional tunneling diagnosis in inappropriate conditions [50].

Additionally, a strong limitation of our study is that a single probe (i.e., the battery failure) was used to infer the occurrence of attentional tunneling. This approach limited the ability to train the ANFIS on a binary reference that does not allow interpretation of intermediate outputs (e.g., TUN = 0.5) from both a mathematical and a cognitive point of view. A possible way to overcome this issue would be to use a dual-task paradigm to derive intermediate levels of attentional focus from the performance on the secondary task (e.g., reaction time and correct response) [51]. The performance would be used as the label to train the ANFIS which, after training, would provide a link between the psycho-physiological measurements and this indicator of attentional focus.

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