Exploring the Decision Tree Method for Detecting Cognitive States of Operators

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Abstract: This study aims to validate a construction methodology of a device able to estimate the cognitive state of an operator in real time.
The SUaaVE project (SUpporting acceptance of automated VEhicle) studies the integration of an intelligent assistant in a level 4 autonomous car. The aim of our work is to model the cognitive state of the driver in real time and for all situations. The cognitive state is a natural state that alters or preserves the operator's ability to process information and to act.
Based on a literature review we identified the cognitive functions used by the driver and the factors influencing them. Different cognitive components emerged from this synthesis: engagement (Witmer & Singer, 1998), fatigue (Marcora and al. 2009) and vigilance (Picot, 2009).
Eye-tracking is a technique used to determine the orientation of the gaze in a visual scene. According to the literature the general dynamics of a visual behavior is characterized by metrics: number of fixations, duration of fixation, gaze dispersion... These dynamics are altered unconsciously due to fatigue (Faber, Maurits, & Lorist, 2012) or hypovigilance (De Gennaro et al., 2000, Bodala et al., 2016); and consciously due to engagement in driving (Freydier et al., 2014; Neboit, 1982).
We carry out a phase of experimentation in a naturalistic situation (driving simulator) in order to collect data for each cognitive state. Realistic scenarios are constructed to induce cognitive states. The model's estimation is compared to the real cognitive state of the driver measured by behavioral monitoring (eye-tracking).
The model is a CARt (Breiman & Ihaka, 1984) decision tree: Classification And Regression Trees. The CARt aims at building a predictor. The interest is to facilitate the design of the tool as well as its future implementation in real time. We illustrate the construction methodology with an example the results obtained.

1 RESEARCH PROBLEM

The SUaaVE project studies the integration of an intelligent assistant in a level 4 autonomous car. This assistant will provide a set of services to enhance the user experience in the vehicle, based on of an assessment of the driver state. In this context, the aim of our work is to model the cognitive state of the driver in real time and for all situations.

2 OUTLINE OF OBJECTIVES

This study aims to validate a device (ALFRED) able to estimate the cognitive state of an operator.

The cognitive model we propose informs ALFRED of the operator's state in real time. The cognitive state is a natural state that alters or preserves the operator's ability to process information and to act. In real time and in a car cockpit, cognitive states are difficult to observe. Their measurement/detection is done in a dynamic, uncontrolled environment (changing luminosity) which is limiting the use of certain sensors. These constraints lead us to choose a specific sensor and tolerant to the effect of the environment: occulometry sensor.

The cognitive model we propose is based on different dimensions: engagement (interest for the road situation, Witmer & Singer, 1998), hypovigilance (Picot, 2009), fatigue (Marcora et al., 2009). Each dimension is discriminated by specific

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ocular behaviors, measurable with an eye-tracker (fixations and saccades).

Each behavior must be coded and integrated into the ALFRED cognitive module. To do so, it is necessary to validate the instrumental efficiency of the eye-tracking data processing for each of the 3 selected dimensions. The results will allow the selection of the most interesting dimension(s) and will guide the development of a real time data processing solution.

3 BACKGROUND

3.1 Definition

A cognitive state is a psycho-physiological state that alters or not the cognitive capacities of the operator. A cognitive state is composed of a set of cognitive dimensions: cognitive load, physical fatigue, expertise in the task, attention, etc. Each cognitive dimension has its own characteristics:

- Role: alert, maintenance, information collection.
- Mechanisms: different levels or phases throughout the day/week/month; regulation by positive or negative feedback, by reaction.
- Effects on the operator's cognitive capacities: induced failures, maintained capacities.

In addition, the cognitive dimensions have interactions between them. There are as many cognitive states as there are possible crossings between the different levels of the cognitive dimensions.

3.2 Constraints

All sensors are not necessarily operational in our context. Indeed, we are confronted with several constraints :

- Tolerance to "noise": ability of an instrument to provide a measurement resistant to undesirable parameters (lighting variations...)
- Portability: ability to be easily transported
- Acceptability: degree of user's acceptance to wear or use the measurement device.
- Ease of implementation: cost, complexity of implementation.

According to the constraints, the sensor must be portable, non-intrusive and noise tolerant. The measurements of the dimensions are behavioral. These measurements must have a sufficient level of acceptability (non-intrusive) and noise tolerance. The operator must not be interrupted.

All these constraints have reduced the field of possibilities. The following cognitive dimensions satisfy these constraints.

3.3 Cognitive Dimensions

Three cognitive states were identified in a literature review:

Engagement in the driving task is a psychological state. It is the consequence of focusing our energy and attention on a coherent set of stimuli and related events (Witmer & Singer, 1998).

Hypovigilance corresponds to the transition between alertness and sleep during which the organism's observation and analysis faculties are reduced (Picot, 2009): decreased attention, increased information processing and decision making time, etc.

Cognitive fatigue is a psychological condition caused by prolonged periods of demanding cognitive activity (Marcora et al., 2009). Cognitive fatigue decreases the individual's ability to perform a task by altering states of alertness and focused attention (Thiffault & Bergeron, 2003).

3.4 Ocular Behavior

Eye-tracking trajectories are composed of fixations and saccades. When a human being focuses on a point of interest, the gaze moves around this area (see Figure 1). The eyes are always moving in our visual environ-ment in order to allow an active vision of the reality around us. This is why a fixation, when we analyze an element, never has a single position of the gaze.

Between two fixations, we make quick movements called saccades. They allow us to position our gaze on the object of interest.

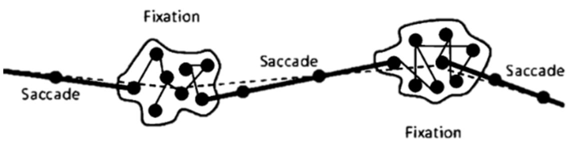

Figure 1: Representations of gaze positions according to the type of ocular event.

3.5 Eye-tracking

❖ Interest of eye-tracking

Eye-tracking is a technique used to determine the orientation of the gaze in a visual scene. According to the literature the general dynamics of a visual behavior is characterized by the following metrics: number of fixations, duration of fixation, gaze dispersion, distance between two saccades, saccade speed, saccade amplitude, and eye deflection angle. These dynamics are altered unconsciously due to fatigue (Faber, Maurits, & Lorist, 2012) or hypovigilance (De Gennaro et al., 2000, Bodala et al., 2016); and consciously due to engagement in driving (Freydier et al., 2014; Neboit, 1982).

❖ Area of Interest (AOI)

Eye-tracking allows us to identify the elements and areas that the driver looks at. The areas of interest (AOI) represent the regular fixation points of a driver (Neboit, 1982 and Freydier, 2014) (Cf Figure 2):

- Interior and exterior mirrors - 3 AOI: "Left mirror", "Right mirror", "Center mirror" ;
- Vehicle Controls - 2 AOI: "GPS", "Steering Wheel" ;
- Speedometer - 1AOI: "Speedometer".

The fixations in the far forward area represent an attention disengagement fixation area: 1 AOI - "Horizon.

Figure 2: Spatial representation of the areas of interest on the reference image of the participants' full visual field.

The cockpit areas do not change location despite the movement of the vehicle. Their static position allows for automated image processing to identify the position of the gaze throughout the experiment. This automated processing requires a reference image (see Figure 2) where all the areas of interest are indicated.

4 METHODOLOGY

The instrumental validation regarding the detection of the cognitive state is based on induction and observation: induction of the operator's cognitive state by the experimental conditions, observation of the ocular behavior. The study of the cognitive model is based on different realistic scenarios constructed to induce cognitive states which will be detailed.

The induction was operationalized on the basis of 3 test scenarios of driving an autonomous vehicle in a simulator, one scenario per induced cognitive dimension: engagement, hypovigilance, fatigue. This induction is based on the information provided by the literature and the adapted environment.

The data associated with the cognitive states are collected during experimental tests in simulation with the objective of collecting oculometric data. The objective is to associate each cognitive state of interest with a typical visual behavior detectable by the oculometric data.

4.1 Participants

40 participants were recruited. Thirty-three participants completed the entire experiment.

Recruitment was done mostly by email via the campus lists of the University of Talence at the following institutions: IMS Laboratory, Bordeaux-INP, INRIA, University of Bordeaux. All of the volunteers were offered a 20 € gift card to participate in this experiment. All gave free and informed consent.

The inclusion criteria for the panel (see A.1) targeted experienced participants, preferably with regular driving experience. The native language must be French to avoid bias in the understanding of the questionnaires. The exclusion criteria (cf. A.2) exclude participants with potential problems of immersion in a virtual reality: epileptic, claustrophobic, cybersickness, etc.

The initial sample included an equitable distribution of gender and age. However, senior adults are more susceptible to simulator sickness (a syndrome closely related to motion sickness), making recruitment more difficult. Table 1 shows the complete study sample.

Table 1: Characteristics (age and gender) of participants.

Age / Sexe	Man	Woman	Total
- 45 years old	21	8	29
+ 45 years old	3	1	4
Total	24	9	33

Our population is 27% female and 73% male, with 88% 45 years old and 12% over 45. Our population is essentially made of men under 45 years old with a proportion of 64% against 9% of men over 45 years old; 24% of women under 45 years old and 3% of women over 45 years old.

4.2 Material

4.2.1 Simulator

- A neutral and silent experiment room (about 8m²),
- Driving seat: ATGP Playseat,
- Logitech G27 driver's station with steering wheel, pedals and gear shift lift,
- Computer with simulation software,
- Simulation software: A.V. Simulation (formerly Oktal) SCANeR Studio™, version 1.8,
- Three high-resolution 32-inch screens (2560 x 1440 pixels). These screens have been aligned to offer an immersion adapted to the 3D scene of the simulation (alignment of lines crossing several screens), and thus reduce the risk of cybersickness.

4.2.2 Sensor

The eye-tracker used is a Tobii Pro Glasses 2 (200Hz): eye-tracker worn binocular. These eye-trackers is worn by the operators as glasses. The binocular eye-trackers is equipped with three cameras: 2 cameras capture the images of the eyes and one camera, called scene camera, captures the visual field of the operator. The scene camera records the video of the environment on which the fixations will be affixed in order to visualize the visual behavior. The horizontal field of view of the scene camera is 60◦.

The glasses are connected to a recording unit via a cable in Micro USB. With an autonomy of 105 minutes the storage media is equipped with an SD card. The unit is connected to the local network via an Ethernet cable.

4.3 Measurement

4.3.1 Independent Variables - Controlled

Cognitive states were considered known and indicated in the data by the variable "Characterization": a categorical variable with three levels, 1 for engagement, 2 for hypovigilance and 3 for fatigue.

4.3.2 Dependent Variables – Observed

The values of the visual metrics depending on the cognitive state are unknown. These are the dependent variables of the model.
Each metric is represented by a numerical variable. They are calculated thanks to the eye-tracker data: position of the gaze in the experimental environment. Eleven metrics have been identified through a literature search (table 2). A metric is calculated over a 20 second window. This window is sliding of one second which makes 11 data per second.

Table 2: List of dependent variables calculated according to the associated cognitive state.

Engagement[1]	Hypovigilance[2]	Fatigue[3]
Fixation frequency in AOI Fixation frequency in the horizon Fixation duration in AOI	Gaze dispersion Gaze dispersion in AOI Distance between two saccades Saccade speed	Fixation frequency Fixation duration Eye deflection angle Saccade speed Saccade amplitude

[1] Freydier and al., 2014; Neboit, 1982
[2] De Gennaro and al., 2000, Bodala and al., 2016
[3] Silvagni and al., 2020; Yonggang Wang and Ma, 2018; Hjälmdahl and al., 2017

4.3.3 Link between Test and Model

The final cognitive model can be written in the form $Y \sim \beta_0 + \beta_1.x_1 + \cdots + \beta_n.x_n + \varepsilon$.

The oculometric data or visual metrics are the dependent variables of the experimental tests: observed variables. In the final model they are the input data: explicative variables x explicatives, independent variable of the model.

The known cognitive state is the independent variable of the experimental tests: controlled variable. In the final model it is the output data: explained variable Y, dependent variable of the model.

4.4 Procedure

After a presentation of the study and a first cybersickness questionnaire, the participant is installed at the driving station. The experimenter presents the controls and indicators of the dashboard, then installs and calibrates the eyetracker. Then the participant carries out the 4 driving scenarios: 1 familiarization scenario in autonomous and manual mode, 3 tests in 100% autonomous. After each scenario, the participant answers questionnaire relating to the cybersickness (Kennedy et al. 1993). If the cybersickness score is suitable (score below 8) then the participant may continue. Before launching the next scenario, the experimenter suggests taking a break. Finally, the participant fills in the socio-demographic questionnaire before being thanked.

4.5 Scenario Setup

The participants' cognitive states are induced by the experimental conditions: environment and cognitive task. 4 test scenarios were constructed: (1) Familiarization with the simulator and autonomous mode; (2) Engagement phase; (3) Hypovigilance phase; (4) Fatigue phase.

❖ Familiarization with the simulator and autonomous mode

This phase is necessary to avoid learning bias by familiarizing the participant with the automatic car controls and the virtual environment. It is carried out before the experimental scenarios.

After explanations on how the simulator works, the participants performes a driving task lasting approximately 15 minutes. In this scenario, the participants drive on all three types of roads for 5 minutes each: city, outskirts and motorway. On the outskirts and the motorway participants are asked to switch on/off the autonomous mode. Using the manual mode allows the user to familiarize himself with the simulator by transposing his driving automatisms.

At the end of the training phase, the participant is able to control the vehicle correctly. Getting back in control, checking the deviation from the axis and checking the indicators remains the usual three points of difficulty.

❖ Engagement phase

This phase has been designed to record the driver's reference eye behavior while engaged in 100% autonomous driving. The scenario presents a variety of road situations and events: other cars, more or less steep country roads, varied landscapes, etc.

❖ Hypovigilance phase

Hypovigilance is characterized by a loss of attention to elements of the situation. It is induced here by a monotonous driving situation (McBain, 1970; Wertheim, 1991), in which the user's attention is little solicited by new events. This scenario is characterized by the following parameters:

- A repetitive environment (Thiffault & Bergeron, 2003): flat terrain; the pines on each side of the road at a frequency of 2 per second, at a speed of 80 km/h; the pines are visible up to the horizon.
- A 15-minute driving task poor in event. The driver has to follow a lane at a constant speed (80 km/h), without changing gears, changing lanes and without using car features (e.g. turn signals, mirrors).
- Few variations in road infrastructure (Larue et al., 2011): no red lights, no stopping, little traffic; no T or perpendicular bends, the road is essentially straight with few curves.

❖ Fatigue phase

The driving scenario is similar to that of the engagement phase. The objective is not to observe hypovigilance but a state of fatigue despite an engaging environment. A constant cognitive load for more than 10 minutes causes cognitive fatigue (Borragán et al., 2016). Cognitive fatigue is induced by performing a difficult n-back task for 15 minutes. Once the 15 minutes of mental effort are passed, the driver checks the trajectory of the car during the remaining 5 minutes, as in the previous stage. This makes it possible to collect ocular data on fatigue.

5 BEHAVIOUR PROCESSING ALGORITHMS

5.1 Pre-Processing of Raw Data

Each cognitive dimension is discriminated by a set of visual metrics calculated from the raw data. The metrics are associated with areas of interest in the environment. To calculate these metrics, several processes are necessary. The first one consists in a filter to detect fixations and saccades, the second one in a mapping to detect events in the areas of interest. The visual metrics are calculated on these mapped data.

5.1.1 Raw Data

The output data of an eye-tracker is presented in an Excel sheet with 200 observations per second. In general, each observation is composed of:

- a timestamp: time in millisecond;
- the direction in x, y and z of the right and left eyes;
- the validity of the detection of the eyes position of the gaze in x and y;
- the frame index of the closest video.

5.1.2 Filtered Data

The offline processing of the raw data is done by the software associated with the eye-tracker: Tobii Pro Lab. The processing is a classification filter for the type of event associated with the gaze position: fixation or saccade. The filter settings are the following:

Table 3: Value of the settings of the filter for the detection of fixations and saccades.

Fixation-Saccade detection filter settings	Parameter values
Max gap length (ms)	150
Noise reduction	moving median, window size (samples): 3
Velocity calculator - window length (ms)	20
I-VT classifier - Threshold (°/s)	35
Merge adjacent fixation - max time between fixations (ms) - max angle between fixation (°)	true 60 0.25
Discard short fixation - Minimum fixation duration (ms)	200

The output data is called filtered data and is associated with an image from the scene camera video. The gaze position is superposed on this video providing a clear replay of the participant's visual trajectories. The filtered data are composed of :

- The position of the gaze: x,y;
- The index of the closest video frame;
- The type of event: fixation, saccade, unclassified;
- The duration of the event in milliseconds;
- The index of the type of eye movement: represents the order in which an eye movement was recorded. The index is an auto-incrementing number starting with 1 for each eye event type.

5.1.3 Mapped Data

Offline processing of the filtered data is also done by the Tobii Pro Lab software. The processing is a mapping detecting the areas of interest in the video images. The objective is to identify the events in the areas of interest. The mapping is performed on a reference image (see Figure 2). This reference image includes all the areas of interest unlike the scene camera which does not have a sufficient field of view. The result of this processing is gaze data mapped on this reference image. The mapped data is composed of:

- The presence of the gaze or not in an area of interest: 0 (absence) or 1 (presence). One variable per area of interest;
- The coordinates of the eye position, x,y on the reference image;
- Confidence score of the mapping: validity score of the mapped gaze points;
- The type of event: fixation, saccade, unclassified;
- The duration of the event in milliseconds;
- The index of the type of eye movement.

A selection of mapped data is applied including a removal of bad mapped events and a removal of outliers. The quality of the mapping is indicated by a confidence score. If the confidence score is less than 0.4, the data is deleted. Beyond this threshold, the loss of data is more than 20%. This adjustment is coherent with respect to the literature (Lemercier and al., 2015; Winn, Wendt, Koelewijn, & Kuchinsky, 2018). Saccades not surrounded by fixation and far from the mean visual field are suppressed. No interpolation was done to avoid adding non-existent information and altering the calculation of metrics.

5.2 Visual Metrics Calculation

Visual behavior metrics are calculated from the mapped and corrected data. Our hypothesis is that the metrics vary with the participant's cognitive state.
The calculated metrics are the dependent variables of the experimental tests. They will be the inputs to our detection model. Eleven metrics were identified as markers of specific cognitive states (Table 2) :

❖ Engagement: 3 discrete variables in the integer space

1. Frequency of fixation in areas of interest;
2. Fixation frequency at the horizon.

The frequencies are the sum of the number of fixations in the areas of interest over a 20 second window.

3. Fixation duration in the areas of interest: average duration of fixations in the areas of interest over a 20-second window.

❖ Hypovigilance: 4 continuous variables in the space of positive reals

1. Dispersion of the gaze in the visual field;
2. Gaze dispersion in the areas of interest.

Dispersions are the average Q3-Q1 interquartile range of the spatial distance between each gaze point (in the AOI) and the median gaze point over a 20-second window. 50% of the observations are concentrated between Q1 and Q3.

4. Distance between two saccades: average of the distances between the end of one saccade and the beginning of another over a 20 second window.
5. Saccade speed: average speed of saccades over a 20-second window.

❖ Cognitive fatigue: 5 variables

1. Fixation frequency: sum of the number of fixations over a 20 second window; discrete variable in an integer space.

2. Fixation duration: average duration of fixations over a 20-second window; discrete variable in an integer space.
3. Eye deflection angle: average of the angle between two vectors formed by the X and Y directions of the eyes over a 20 second window; continuous variable in positive real space.
4. Saccade speed: average speed of saccades over a 20-second window; continuous variable in positive real space.
5. Saccade amplitude: average of the distances between the beginning and the end of the same saccade over a 20 second window; continuous variable in the space of positive reals.

All metrics were calculated over the three phases of the scenario: engagement, hypovigilance and fatigue. Each metric is calculated over a 20-second window. This 20 second window slides by one second which makes 11 observations per second per phase per participant.

It is necessary to know the behavior of the metric on all phases to characterize differences between phases.

6 FIRST RESULTS

The model is a CARt decision tree built on the data set. The set of independent variables of an individual classifies him in a cognitive state.

6.1 Method of Analysis

The Classification And Regression Trees - CARt (Breiman & Ihaka, 1984) are supervised learning methods. The tree tries to solve a classification problem. Mathematically speaking, the method performs a binary recursive partitioning by local maximization of the heterogeneity decrease.

The CARt aims at building a predictor: predicting the values taken by our dependent variable Y (cognitive state) as a function of the independent variables X (visual metrics).

This prediction is based on a tree where each node corresponds to a decision about the Y value. This decision is made according to the value of one of the Xs. At each node, the tree splits the data of the current node into two child nodes. The individuals are divided into the two most homogeneous subsets (Gini diversity index) possible in terms of Y. The first nodes use the most important variables. Not all metrics are necessarily used in the construction of the tree. A significant variable is not used if another is highly correlated with it. The terminal leaves give the predictions of Y.

The independent and dependent variables can be quantitative or qualitative. Here the independent variables are quantitative. The dependent variable is categorical at three levels: 1 for engagement, 2 for hypovigilance and 3 for fatigue.

6.2 Dataset

3 recordings corresponding to the 3 tests scenarios are associated with each participant. The scenarios are divided into two periods. The first provokes the desired cognitive state, which is observed during the second. The first period provokes a cognitive state that is under-adjusted due to the chosen environmental conditions. The second period is the moment when the participant is actually in the desired cognitive state. The learning phase is not included in these two periods. The periods of interest occur at different times (minutes) depending on the scenario:

- Scenario 1: observation of an engaged participant during the next 3 minutes of the scenario.
- Scenario 2: induction of hypovigilance during the first 15 minutes of the scenario; observation of a hypovigilant participant during the next 3 minutes of the scenario.
- Scenario 3: Induction of fatigue during the first 15 minutes of the scenario; observation of a tired participant during the next 3 minutes of the scenario.

Metrics calculation are done on the second periods of the scenarios. A data is composed of the value of the 11 metrics for one second for a participant. This makes a total of 17,820 data: 33 participants, 3 test scenarios, 180 seconds. The data does not have to be normalized. All these data are the dataset for the construction of the CARt.

6.3 Decisional Tree

The decision tree (Figure 3) was built with the rpart package. First, the tree was built on all the data with the tree building function rpart() of the package. We keep the default parameters. The learning error is 48%.

In figure 3, we can read the tree as follows. At the root of the tree there is a node that splits into two branches: branch 1 on the left and branch 2 on the right. Branch 1 corresponds to the participants' data such that the “number of fixations on the horizon” exceeds the threshold of 11.5 fixations / 20 seconds.

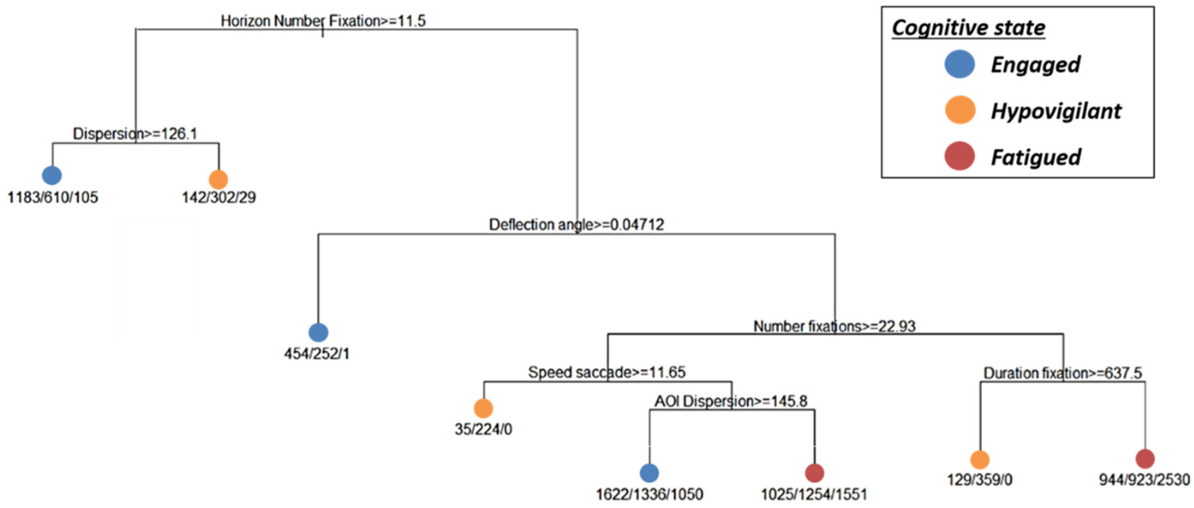

Figure 3: First version of the CARt for the detection of the cognitive state of the operator, construction of the data set.

Branch 1 splits into two end leaves: leaf 1 on the left and leaf 2 on the right. Leaf 1 corresponds to the data of participants such that the "gaze dispersion" exceeds the threshold of 126.1 pixels / 20 seconds. In this leaf 1 the cognitive state detected is engagement.

The 3 indicators under the end leaf indicate the distribution of the participants' data classified in this leaf according to their actual cognitive state: engaged/ hypovigilant / tired.

1183 data from engaged participants are classified as engaged; 610 data from hypovigilant participants are classified as engaged; 105 data from tired participants are classified as engaged. Here the number of correct classifications prevails by 62%.

Leaf 2 corresponds to the data from participants such that the gaze dispersion does not exceed the threshold of 126.1 pixels / 20 seconds. In this leaf 2 the cognitive state detected is hypovigilance. 142 data from engaged participants were classified as hypovigilant; 302 data from hypovigilant participants are correctly classified as hypovigilant; 29 data from fatigued participants are classified as hypovigilant. The number of correct classifications prevailed by 63%.

The determination of the operator's cognitive state stops when the reading of the model results in a terminal leaf. The model always determines an output. If the operator is not in one of these three states the model returns the closest cognitive state.

6.4 Predictive Quality Validation

The cross-validation method (Mosteller & Tukey, 1968) partitions the data into 3 subsets. Each subset is successively used as a test sample, the rest as a learning sample: 2/3 for learning and 1/3 for testing. The tree, our estimator, is computed on the training data. The prediction error is calculated on the test data. At the end of the procedure, we obtain 3 performance scores: percentage of error. The mean and the standard deviation of the 3 scores respectively estimate the percentage of error and the variance of the validation performance.

The three performance scores obtained are: 65%, 67% and 67%. This makes an average of 66% and a standard deviation of 0.0011. We find that, as it stands, the model does not perform well enough to accurately predict the values of the cognitive state variable Y.

In order to improve our model, as we explain in paragraph 7, a descriptive study of the data is in progress. Our objective is to identify possible outliers that would decrease the performance of the model.

7 EXPECTED OUTCOME

The objective of our approach is the construction of an efficient detector tree with a test error of about 20%.

Analyses are in progress and will allow the realization of a satisfactory predictive tree. New data sets are built from existing data such as the exploration of the variations of visual metrics. The variations are calculated in points and in percentages for each individual. If the percentage variations are significant, the intra-individual difference is important. The realization of a single tree per operator is considered.

Automatic classification of a group of individuals for each cognitive state is planned. The objective is to identify groups of individuals and operator profiles. The hypothesis is that the inter-individual difference is too important for the realization of a general model for all operators.

A sub-model of fatigue will be developed to enable the concomitance of several cognitive states to be addressed.

8 CONCLUSION

Our research aims at defining a method to design a predictor of the cognitive state of operators based on their visual behavior. The interest is to facilitate the design of the tool as well as its future implementation in real time. In this paper, we present the methodology for the conception of the predictor and illustrate with an example the results obtained. Our objective is twofold. The first one is the development of a performant predictor; the second one is the application of this method on future eye-tracking data. In the second case, it will allow the improvement of the predictor by the integration of new data for the detection of other cognitive states: physical fatigue, mental load, attention.

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APPENDIX

A.1 The Inclusion Criteria Were:

- Possession of a driver's license for at least 2 years and 2500 km driven.
- Regular driving preferred
- Native French speaker
- Normal vision, or corrected by lenses (not corrected by glasses)

A.2 The Exclusion Criteria Were:

- Heart problems, people with epilepsy/ photosensitivity/ claustrophobia/ balance problems, history of neurological or psychological problems
- Taking medication or drugs that affect the sleep-wake cycle.