

Brain-Computer Interface using P300: A Gaming Approach for Neurocognitive Impairment Diagnosis

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Abstract—This paper proposes a novel mobile healthcare system for remotely monitoring neuro-cognitive functions of impaired subjects and proposing possible treatments. Currently, only hospital centers perform similar analyses through fixed and wired electroencephalography (EEG) inspection. The solution proposed here works wirelessly and improves its accuracy learning by performances of the subject playing a game/test. The system is based on spatio-temporal detection and characterization of a specific brain potential named P300. It includes: i) a wearable wireless EEG device; ii) a gateway (tablet or smartphone) processing gathered data, also providing the test/game to the user. Given the above hardware settings, a new algorithm, named tuned-Residue Iteration Decomposition (t-RIDE), provides spatio-temporal features of P300s and a semantic-based reasoner allows taking into account factors which could modify the test if performed in non-standard conditions. The system has been adopted with 12 subjects involved in three different cognitive tasks with increasing difficulty. Fast diagnosis of cognitive deficits is reached, including mild and heavy impairments cases: t-RIDE processing is performed in 1.95s (after 79 iterations for convergence) whereas semantic matchmaking routine requires 2.5ms in the worst case. A case study for an Alzheimer injured patient is reported to corroborate and clarify the proposed approach.

Keywords —Mobile Health-Care, P300, t-RIDE, EEG, ERP, Semantic-based Matchmaking.

I. INTRODUCTION

Worldwide, nearly 44 million [1] people have Alzheimer's or a related dementia, although only 1-in-4 people with this disease is early detected [1]. Recently, a novel paradigm for non-invasive low-cost analysis based on the characterization of Event-Related Potentials (ERPs) opens new scenarios for the early diagnosis, monitoring and rehabilitation of people affected by neurocognitive impairment. At this aim, the most studied ERP component is the P300, a large positive deflection in EEG signal reaching its peak around 300ms after a relevant stimulus (see Fig. 1). It reflects a stage of stimulus classification and is excitable by the oddball paradigm, in which low-probability event, named "target" are shown together with high-probability ones [2]. P300 characterization is strictly related to the cognitive state of the subject under test [2]. Literature studies [3-12] demonstrate the possibility to exploit P300 for brain computer interface (BCI) applications. The "P300 Speller", for instance, firstly designed by Farwell et al. [3], is based on P300 classification and allows tetraplegic and paralytics subjects to communicate. While a P300 BCI for the implementation of a brain-actuated wheelchair has been investigated by Iturrate et al. [4], M. Duvinage et al. [5] reported the design of a P300 based prosthesis.

The low invasivity and the low cost of the P300 BCI applications have led to a P300 based games ("neurogames") for entertainment, i.e. the "MindGame"[6] or "Brain Invaders" [7], where the movement of a virtual character are controlled by the brain activity of the user. It is notable that the above mentioned BCI applications are just few of the numerous remarkable P300 based solutions. Several solutions have been already proposed in the literature [8, 9] for P300 extraction: currently, the most commonly used algorithms to measure and characterize the P300 potential in a clinical environment are the 'grand average', the Independent Component Analysis (ICA) [10] and the Principal Component Analysis (PCA) [11]. They drive to the adoption of the tuned - Residue Iteration Decomposition (t-RIDE) approach proposed in [12].

In this paper, we present a first of a kind (to the best of our knowledge) P300 BCI-based game/test for remote diagnosis and treatment of dementia. The system is made up by a hybrid single-trial and averaged-trials approach of P300 detection, classification and spatio-temporal characterization. The system includes a first step of Machine Learning (ML) based on the t-RIDE algorithm developed in [12] in order to extract spatial (e.g., topography) and temporal (e.g., latency and peak) parameters of P300 potential. A phase of features extraction and threshold definition completes the ML stage. The system has been developed to deliver to the patients under test, a three-level game/test, complying with the oddball protocol. The game/test is driven by a synchronous Brain-Computer Interface (BCI) system that adapts in *real-time* the difficulty degree of the game to the patient's ability in target stimuli discrimination, using a thresholds linear classifier. Since the game can be performed in a domestic environment, the presence of external factors can heavily affect the P300 measurements. The possible P300 modulations (due to the low repeatability of the measure) are taken into account and corrected by a semantic-based matchmaking algorithm: the implemented knowledge representation and reasoning techniques identify and filter the disturbance of a domestic scenario by providing an automated real-time assessment of the cognitive test outcomes.

The proposed system exhibits several advantages compared to the techniques currently in use for this type of test. The test can be performed remotely improving the life quality both of the patient both of his/her caregivers. It promotes the de-hospitalization, reducing the related costs. The test itself is a game: this increases the degree of comfort for the patient. Moreover, the game is adaptive allowing accurate evaluation of the patient excursus. The system corrects the factors, which could modify the P300.

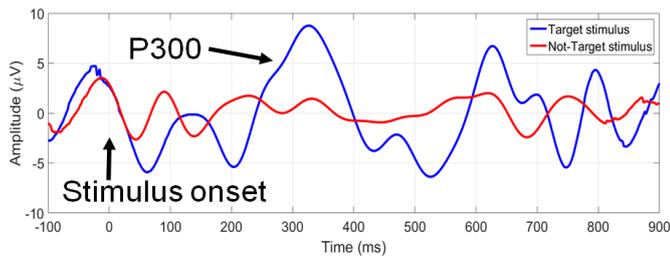


Fig. 1. Time-domain P300 waveform (blue) recorded on a healthy subject compared to inconsistent pattern of Not-target stimulus ERPs (red) on a single EEG channel (P_z).

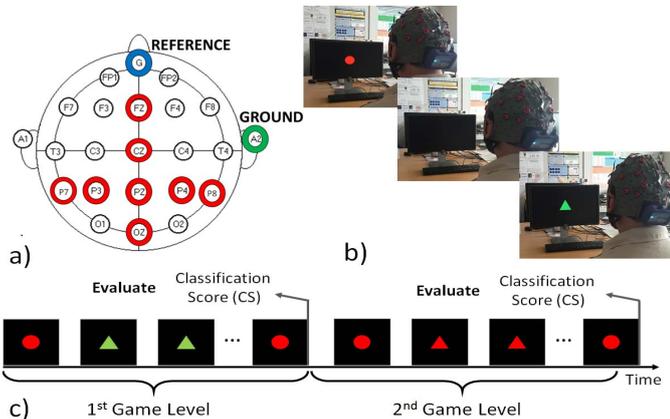


Fig. 2. a) Channels of interest (in red) according to the international system 10-20. In blue the nasion reference and in green the ear-lobe ground b) Illustration of the experimental setup c) A time close-up of the first two levels (three levels are available) of the game proposed from the system.

The processing is supported by custom algorithms, which overcome the limits of the state of the art technology [12]. The paper is organized as follows. Section II describes the system architecture, focusing on both hardware, ML and BCI algorithms. Section III presents the experimental results coming from *in vivo* measurements and consequent diagnosis on 12 subjects (age 26.5 ± 3.5). Section IV outlines the merit of the here proposed technique and concludes the paper.

II. SYSTEM ARCHITECTURE

The proposed system, named *m-Health*, combines diagnostic and rehabilitation aspects in a single architecture that provides a pervasive and continuous interaction between physician and patient. The patient wearing a wireless EEG headset performs autonomously at his/her home the adaptive game/test. The game is completely guided by the software in a ‘plug and play’ fashion. In the classification (ML) phase, the system proposes the patient three *different* visual odd-ball tasks with an increasing difficulty. These tests individually last about 180 seconds (36 target stimuli in 1:4 ratio with standard ones) in order to achieve a calibration for the following usages of the game. Once the calibration is completed, no more learning stage is required. The t-RIDE algorithm processes the acquired EEG data as soon as the game difficulty increases. The difficulty level is driven by the on-line BCI system, which compares - after classification - the number of recognized target stimuli, during a single level, to the relative overall number of proposed

target items. Their ratio identifies a Classification Score (CS). If CS exceeds 0.8 (80% accuracy in target discrimination skill for a single game level), the game evolves dynamically to the next level. t-RIDE outcomes are subsequently interpreted by a semantic-based reasoner to correlate P300 amplitude and latency to the particular test conditions, including the clinical history of the patient.

Since the game includes three different levels, three medical reports (in pdf format) are created and then cloud-shared with the physician. The report contains the spatio-temporal P300 characterization, the semantic-based reasoning results, the overall CS and the number of recognized target stimuli for each task. The system also identify and quantify the P300 evolution by comparison with games’ history (the previous output files are never deleted).

A. Experimental and Data Processing setup

Dataset. Twelve healthy subjects, with age between 23 and 30, participated in the experiment to test the system. The group was selected with a high level of homogeneity in terms of age and schooling. Fig 2.c illustrates the stimuli presented to the subjects.

Hardware. Data are acquired with a 32-channels wireless EEG headset with active electrodes (conditioning integrated circuit are embedded in the electrode performing amplification, filtering and digitalization) as the one used in [13-15]. The EEG recordings have been performed using eight electrodes (Fz, Cz, Pz, Oz, P7, P3, P4, P8 – in red in Fig. 2.a) referenced to AFz electrode (in blue in Fig. 2.a) and right ear lobe (A2 – in green in Fig. 2.a) is used as ground.

EEG signals are recorded with sample rate 500Hz, 24-bit resolution, $\pm 187.5\text{mV}$ input range and filtered using a bandpass (Butterworth, 8th order 0.5-100Hz) and a notch (Butterworth, 4th order 48-52Hz) filter (embedded into the front-end). The recording scheme is monopolar. The positions of electrodes are in line with the international 10-20 standard for EEG data acquisition. The EEG signals are recorded during the test and are synchronized with the delivered stimuli by the gateway. In the experimental evaluation, the gateway has been assumed as a PC (Intel i5, RAM 8 GB, 64 bit) which collects EEG data, generates and delivers the game and performs data processing by a customized Simulink model.

Pre-processing. The pre-processing aims to reduce both noise and artifacts such as eye movements and head movements, avoiding critical drifts of the P300 waveform. Data pre-processing is performed on each monitored channel. Considering a single-channel pre-processing chain, the acquired signal is low-pass filtered (Butterworth, 6th order, $f_{\text{stop}} = 15\text{Hz}$) and aligned to the stimulus signal. Subsequently, the EEG signal is decomposed in epochs of 1s. Each epoch -also named single-trial-starts 100ms before the rising edge of the stimulus and ends 900ms after. Epochs are fitted in a 6th order polynomial (with Bisquare weights), *i.e.*, the highest that eliminates the slow trends without modifying the ERP patterns. The resulting curve is subtracted from the EEG signal that is then centered (offset cancellation) and normalized.

B. Features Extraction and Classification

The ML phase of the proposed system exploits the *window optimization* of t-RIDE algorithm to extract an accurate latency value, *i.e.*, the most probable subjective single-trial P300 time occurrence. Due to the subject-to-subject P300 variability, the learned latency is used for a single-trial classification. The classification is based on features extraction and hyper-dimensional threshold-based linear decision. The linear thresholds classifier has been selected due to its balanced compromise between accuracy and computational lightness [16].

According to specialized medical staff P300 visual inspection guidelines, five features have been extracted covering time-domain shape information and dissimilarity between target and not-target response. The selected features are described in the following.

- *F1. Symmetry*: a normalized index that quantifies the symmetry of the signal with respect to the central reference. It can be expressed as (1):

$$f_1 = \frac{2}{ns-1} \sum_{i=1}^{ns} [x(i) - x(ns-i)] \quad (1)$$

where ns is the number of considered data points.

- *F2. Peak to Peak difference*: a normalized index which detects how close is the maximum point of the single trial to the middle of the plot. It can be expressed as (2):

$$f_2 = \frac{\frac{(ns+1)}{2} - \left| \frac{(ns+1)}{2} - \text{index}(\max(x)) \right|}{\frac{(ns+1)}{2}} \quad (2)$$

- *F3. Slope changes*: returns a score on how many times the direction change. A small number of changes is preferable. It can be obtained by counting the number of zeros of the signal's derivative that represent the slope sign changes.
- *F4. Inscribed Triangle area*: provides the area of a triangle built into the P300 deflection and denoted as f_4 in (3):

$$f_4 = \frac{1}{2} \cdot \det \begin{bmatrix} x_1 & y_1 & 1 \\ x_2 & y_2 & 1 \\ x_3 & y_3 & 1 \end{bmatrix} \quad (3)$$

where (x_2, y_2) is the maximum value of the extracted data points, (x_1, y_1) is the minimum value of the left side of the extraction and (x_3, y_3) is the minimum value of the right side ones.

- *F5. Convexity*: a boolean flag that identifies the convexity of data points. Formally (4):

$$f_5 = \begin{cases} 0 & \leftrightarrow \sum_{i=1}^{\left(\frac{ns}{2}\right)-1} \frac{\partial x(i)}{\partial i} \leq \sum_{i=\left(\frac{ns}{2}\right)+1}^{ns} \frac{\partial x(i)}{\partial i} \\ 1 & \text{otherwise} \end{cases} \quad (4)$$

The above features are extracted either in an off-line phase via ML and in the further real time classification. The features calculated with ML are used as threshold values to be compared with the ones extracted on-line during the classification phase. ML thresholds for each feature are obtained through statistics (median, 25th and 75th percentiles extraction) on data vectors. The ML algorithm extracts a percentage of P300 detection rate on each monitored channel.

In the real-time application, when a stimulus occurs, the system extracts the features from the single-trial for each channel and compares them with learned threshold values. For each feature,

if it is within the reference value, a Boolean flag is raised to one. For each channel, a score is computed consisting in a weighted sum of all the flags, according to Eq. (5):

$$\text{Score}_i = w_1 \cdot F_{1,i} + w_2 \cdot F_{2,i} + w_3 \cdot F_{3,i} + w_4 \cdot F_{4,i} + w_5 \cdot F_{5,i} \quad (5)$$

where the index i refers to a given channel, $F_{j,i}$ represents the flag related to the j -th feature on the i -th channel and $(w_1, w_2, w_3, w_4, w_5)$ is the set of weights. The weights are customizable but their sum must be 1. To each feature is assigned a score of 1 or 0.5 if it overcomes the higher threshold or only the lower one, respectively. In order to speed up the computation, the real-time feature extraction is performed on a down sampled (from 500sps to 250sps) and windowed (M samples centered on the learned latency, $M = 77 \sim 310$ ms in this work) version of the signal. Finally, the system operates a spatial and amplitude validation of the reached score. The spatial validation verifies the simultaneous occurrence of P300 presence flag on the 75% (6 electrodes on 8 available) of the monitored brain extension, w.r.t. channels which deliver a high detection rate. Additionally, the score is validated only if the detected P300 do not exceed the amplitude thresholds (upper and lower bounds) learned during the ML.

C. The Adaptive Game

According to [17], the implemented cognitive game aims to accurately evaluate the patient's cognitive status. The game does not require an active response to the stimulation, making it a no-go task. Subjects are required to recognized rare target stimulus among the not-target ones.

Initially, the patient does not know which will be the target stimulus in the game level: s/he progressively realizes that during the game. This approach has the aim to maintain a high level of attention, preventing the *habituation* phenomenon often compromising the final diagnosis [18]. Furthermore, the system provides a quantitative analysis based on game history that creates a motivating and challenging environment. During the test, the patients are asked to reduce eye movements, blinking, head and body movements, as well as jaw contractions, in order to reduce artifacts. According to [17], the game levels are modeled on the simplest odd-ball version for visual stimulation. For all the levels, the patients are asked to identify and count the occurrence of the less frequent stimulus.

First Game Level. Circle and triangle are randomly flashed on a black screen and repeated. Their color is, at this game stage, strongly different (in Fig 2.c, the target is a red circle and the not-target is a green triangle). The flashing stimuli are randomly presented with non-uniform probability. The target stimulus probability is 20%. The Inter-Stimuli Interval (ISI) is randomized and has a uniform distribution ranging from 1s to 2s. Each visual stimulus persists on the screen for 200ms. The subject distance from the screen should be approximately 1.5m to give both better view *and postural comfort*. The time duration of each game level is typically 75s (it allows to present circa 15 target stimuli and more or less 60 not-target ones).

Second Game Level. When this game level occurs, the system eliminates the chromatic difference between the stimuli and randomly reassign the shapes (square and triangle) to target and not target. The probability values is retained as well as ISI and

stimulus duration setup. The cognitive difficulty is increased as the human brain classification capability will be driven only by the geometrical shape discrimination now.

Third Game Level. Preserving all configurations of previous levels, in the third level the discrimination is still geometric but the shapes are very similar (non-target: red circle; target: red ellipse).

Currently, the game is composed by only three levels, but the versatility of the Simulink model, that generates it, makes the game open to new levels and new challenges (*i.e.*, Kanizsa illusory odd-ball visual task [19]). The time duration of the overall game is 225s (with circa 45 target stimuli and more or less 180 not targets). If there are no relevant differences between the response to target and not target stimuli in terms of signal features, data for calibration is lacking. Hence, automatically the game starts a single level calibration and operate a ML phase on this acquisition.

D. Diagnostic tool

The diagnostic unit of the architecture is entrusted to t-RIDE algorithm, widely treated in [12], due to its accuracy in spatial-temporal characterization of P300 potential. As proven in [12], t-RIDE results reach an accuracy greater than 90% with only 12 stimuli. Calculation is performed on all channels as soon as the game difficulty increases. A statistical analysis of gathered data informs the physician about the medium latency and peak for each channel. The P300 characterization output files consist of:

- i) Figures of time-domain waveforms of target stimuli compared to non-target for each channel and task.
- ii) Topography about the P300 amplitude and latency evolution.
- iii) Tables expressing presence/lacking of P300, peak values and latency values for each channel and task.

E. Semantic-based Automated Test Correction

In order to enhance t-RIDE diagnostic performance, P300 characterization is further processed by a knowledge-based deduction engine. It gives an automated assessment of the test outcomes and, in case, identifies factors to improve it.

In a generic knowledge-based application formally grounded on Description Logics [20], a matchmaking between a request Q and a resource R allows calculating their semantic distance w.r.t. a shared terminology (ontology). In this way, it is possible to rank the best matching resources R_i for a given request Q . Basically, a non-standard inference procedure is adopted for that, namely Concept Abduction [21]: in the working prototype we devised it is implemented by the Mini-ME embedded reasoner [22]. A semantic-based test description is considered as request Q and is matched against a set of outcome “templates”, representing the available resources R_i . Q models the neuro-cognitive test context (time of day, features of the test environment, etc.), subject’s conditions (including age, sex, diseases, ongoing treatments and sensory impairments) and finally the test response P300 amplitude and latency (supplied by t-RIDE). In addition, a set of semantic annotations of cognitive test outcome “templates” populate a Knowledge Base (KB). The templates include five outcome classes – from “excellent” to “critical” – for assessing the subject’s performance, and two descriptions of corrective actions on the

outcome related to subject’s conditions and test context, respectively. Concept Abduction is employed to discover both the closest outcome type and the most suitable corrective actions for a given subject in a given context (test description). If Q does not match R_i fully, Concept Abduction extracts which hypothesis H should be made about R_i to reach a full match and calculates the related semantic distance.

Abstracting from raw data to semantic annotations consists of mapping each attribute of current test to a class in the ontology and assembling the test description as logical conjunction. By modeling both ontology and annotations properly (see further Sec. III.B for an illustrative example), the semantic distances allow detecting the test outcome type automatically, while the hypotheses return the corrective factors to improve the test results.

III. RESULTS

Results of experiments carried out on 12 healthy subjects (age 26.5 ± 3.5) are presented in Table I. It recaps measured P300 peak amplitude and latency values as well as the most affected electrodes for each subject, w.r.t. different game levels. For the first game stage, the P300 amplitude ranges from 2.8 to $8 \mu\text{V}$ with a mean value of $4.7 \mu\text{V}$ and a 0.61 standard deviation, the P300 latency in the first level is included in the range 301 – 402ms, with a mean value of 349.25ms and a standard deviation of 35.52ms. Similarly, for the second level, P300 amplitude ranges from 3 to $6.5 \mu\text{V}$ with a mean value of $4.39 \mu\text{V}$ and a 1.16 standard deviation; latency ranges from 332 to 390ms, with mean value of 360.75ms and a standard deviation of 15.40ms. Finally, for the third game level, P300 amplitude ranges from 2.5 to $6.3 \mu\text{V}$ with a mean value of $4 \mu\text{V}$ and a 1.23 standard deviation; latency ranges from 364 to 398ms, mean value of 377.5ms and standard deviation of 15.54ms. Table I shows a general P300 degradation when the game difficulty increases. The P300 amplitudes decrease while latency times increase: amplitude values decrease on average (considering all subjects degradation trend) of $0.21 \mu\text{V/LVL}$ (MIN: $0 \mu\text{V/LVL}$ MAX: $1.3 \mu\text{V/LVL}$); latency values increase on average of 16ms/LVL (MIN: 5ms/LVL , MAX: 36ms/LVL). In addition, Table I show that cortical area involved by the P300 shifts from the central-parietal to the central-frontal when the game difficulty increases.

A. Classifier Results

The proposed linear threshold classifier has been calibrated (ML phase) on a sample of 36 target responses (test duration: 198s) at the second level difficulty of the game. Subsequently, it has been tested on a *training* game composed by 38 target responses and 156 not-target ones. The accuracy in P300 detection reached 86.84% on average.

Target single-trials have been detected with 92.1% accuracy while not-targets ones return 18.4% of false positives (and thus 81.6% of recognized not-target trials). The worst classification case has led to an overall accuracy of 81.6%. Although the accuracy of the proposed classification is lower than other approaches in literature [16], its computational effectiveness makes it of a particular utility for a time-constrained application as the one we devised.

t-RIDE characterization

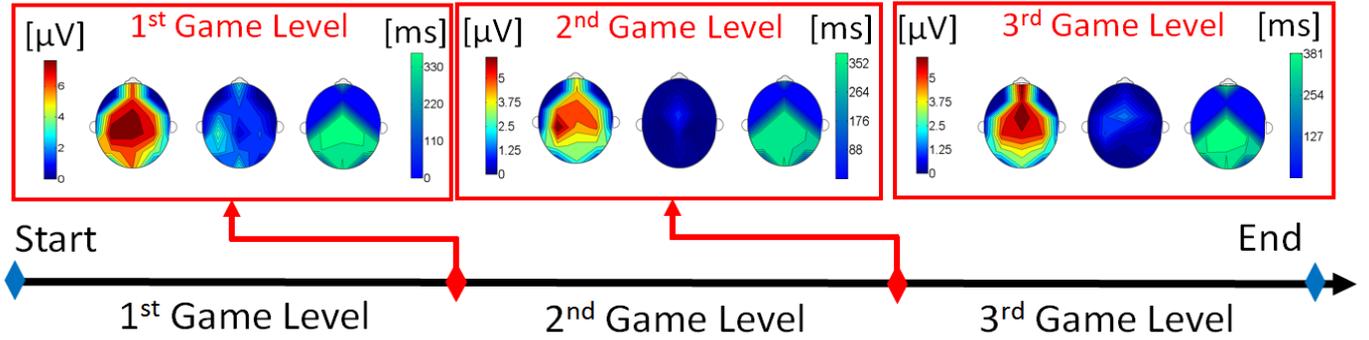


Fig 3. Temporal diagram of game evolution supported by extracted t-RIDE spatio-temporal characterization. Each red diamond identifies the instant when the difficulty increases and the game level changes. In red boxes, target amplitude, non-target amplitude and latency topography are shown. P300 was detected on the 100% of the subjects and typically is more evident in the central-parietal electrodes.

TABLE I. P300 SPATIO-TEMPORAL CHARACTERIZATION VALUES

Sub	1st Game Level			2nd Game Level			3rd Game Level		
	Amp (μV)	Lat. (ms)	Top.	Amp (μV)	Lat. (ms)	Top.	Amp (μV)	Lat. (ms)	Top.
1	4	301	F _z C _z	4.1	340	C _z P _z	3.8	370	C _z P _z
2	4.4	348	P _z P ₄	3.7	371	P _z C _z	3.3	379	F _z C _z
3	8	341	P _z C _z	6.5	348	P ₃ C _z	6.3	375	F _z C _z
4	3.5	368	P _z O _z	3.5	368	P _z C _z	3.2	374	P _z C _z
5	2.8	347	F _z C _z	3	359	F _z C _z	2.5	376	C ₃ C _z
6	3.1	402	F _z C _z	3.1	358	F _z C _z	2.8	377	F _z C _z
7	4.5	321	P _z C _z	4.3	364	C ₃ C _z	4	392	C ₃ C _z
8	7.6	362	P ₃ C _z	5.8	366	C ₃ F _z	5.1	371	C _z F _z
9	3.7	315	P _z P ₄	5	361	P _z P ₄	3.6	365	O _z P ₄
10	5.8	345	F _z C _z	6	332	F _z C _z	4.2	364	F _z C _z
11	3.6	401	F _z C _z	3.7	390	P _z C _z	3.4	398	C _z C ₄
12	3	380	F _z O _z	4	372	P _z O _z	6.2	389	P _z C _z

TABLE II. INTER-SUBJECT ACCURACIES

SUB.	1	2	3	4
1	86.84	36.84	21.35	34.40
2	47.50	81.60	34.57	9.85
3	12.41	32.71	85.51	17.23
4	40.20	10.75	18.21	86.21

Typically, a real-time features extraction and classification lasts 2.4ms (5 features · 0.06ms/feature on 8 channels) including spatial validation. In the worst measured case, the classification has reached 14.4ms (0.3ms/feature): if compared with a widespread robust approach for P300classification [23], the proposed system reduces the response time about 25 times, losing the 4% of the accuracy on the same dataset.

In order to highlight the P300 modifications in different subjects, the data of each patient have been tested adopting the features thresholds set for other patients. The results are shown in Table II (where only four subjects have been reported for the sake of brevity). The diagonal elements are accuracies when a subject is tested adopting his/her classification model; low values of the off-diagonal elements indicate the high degree of patient specificity in the classification. This finding confirms the need of a leaning phase due to the possibility that the P300 signals may be significantly different between different subjects.

B. Case study

A toy case study is reported hereafter to better explain how the semantic-based game adaptation works. Examples are purposely simplistic and a logic-based notation has been adopted. The reader unfamiliar with that formalisms could be referred to [20] for more details, anyway the general meaning of logic operators and annotation conjunct is quite intuitive. Jim – fictional name – is an 86-year-old man with dementia, anxiety disorder, osteoporosis and poor hearing. He is taking the neuro-cognitive game in the afternoon at home (a pleasant and familiar environment) while in an agitated state. Jim runs the test and t-RIDE extracts a P300 amplitude of 3.1μV and latency of 401ms. This corresponds to the following test description with respect to the devised domain ontology (not reported for brevity):

$Q: \exists \text{ has_Sex } \neg \forall \text{ has_Sex.Male} \neg \exists \text{ has_Age } \neg \forall \text{ has_Age.Old} \neg \exists \text{ has_Disorder } \neg \forall \text{ has_Disorder. (Osteoporosis } \neg \exists \text{ Anxiety_Disorder)} \neg \exists \text{ has_Hearing } \neg \forall \text{ has_Hearing.Poor_Hearing } \neg \exists \text{ has_Eyesight } \neg \forall \text{ has_Eyesight.Average_Eyesight } \neg \exists \text{ has_Day_Time } \neg \forall \text{ has_Day_Time.Afternoon} \neg \exists \text{ has_Mood } \neg \forall \text{ has_Mood.Calm} \neg \exists \text{ has_Location } \neg \forall \text{ has_Location. (Home } \neg \exists \text{ has_Location_Property } \neg \forall \text{ has_Location_Property.Pleasant_Location)} \neg \exists \text{ has_Amplitude } \neg \forall \text{ has_Amplitude.Poor_Amplitude } \neg \exists \text{ has_Latency } \neg \forall \text{ has_Latency.Critical_Latency}$

The KB takes five test outcome profiles mainly considering P300 response. In order to detect the impairing factors, the above Q is further compared with the following two descriptions, referring to environmental and subjective factors respectively.

$R1: \exists \text{ has_Time_Time } \neg \forall \text{ has_Day_Time.Morning } \neg \exists \text{ has_Feeding_Status } \neg \forall \text{ has_Feeding_Status.Well_Fed} \neg \exists \text{ has_Mood } \neg \forall \text{ has_Mood.Calm } \neg \exists \text{ has_Location } \neg \forall \text{ has_Location. (} \exists \text{ has_Location_Property } \neg \forall \text{ has_Location_Property. (Familiar_Location } \neg \exists \text{ Pleasant_Location } \neg \exists \text{ Mild_Temperature_Location))}$

R1 models favorable test conditions, including morning time, a well-fed state, calm mood and a familiar, pleasant and mild-tempered location.

TABLE III. SEMANTIC MATCHMAKING TIME (in ms)

Step	Average	Standard deviation	Worst
KB loading	133,745	31,454	227,118
Request 1	0,397	0,068	0,580
Request 2	0,493	0,052	0,604
Request 3	1,335	0,547	2,415

R2: $\exists has_Age \wedge \forall has_Age.(Young \wedge Adult) \wedge \forall has_Disorder.(\exists treated_With \wedge \forall treated_With.(Not_Antidepressant \wedge Not_Anxiolytic \wedge Not_Mood_Stabilizer)) \wedge \exists has_Eyesight \wedge \forall hasEyesight.Good_Eyesight$

R2 models the ideal subject's conditions, such as young-adult age, good eyesight and no psychiatric medications undermining focus and attention. Computed hypotheses are:

H1: $\exists has_Time_Time \wedge \forall has_Day_Time.Morning \wedge \exists has_Feeding_Status \wedge \forall has_Feeding_Status.Well_Fed \wedge \exists has_Location \wedge \forall has_Location.(\exists has_Location_Property \wedge \forall has_Location_Property.Mild_Temperature_Location)$

H2: $\exists has_Age \wedge \forall has_Age.(Young \wedge Adult) \wedge \exists has_Disorder \wedge \forall has_Disorder.(\exists treated_With \wedge \forall treated_With.(Not_Anxiolytic)) \wedge \exists has_Eyesight \wedge \forall hasEyesight.Good_Eyesight$

In H1 only test time is different from Q, while other reported elements are just missing in Q: since semantic matchmaking is based on the Open World Assumption, they are not in contrast but are just unspecified information. Conversely, H2 is equal to R2: all subjective criteria are adverse in this case. In particular, ontology models anxiety disorder as requiring treatment with anxiolytics, which can impair neuro-cognitive performance.

In this setting, the semantic distance score (*semDist*) can be interpreted as a measure of the amount of corrective actions to be taken – if possible – for improving the test outcome. Intuitively, *semDist* = 0 in case of a full match (no correction needed), whereas it takes the greatest value when comparing Q with the most generic concept (Top) of the ontology (root of the taxonomy). Therefore:

$$Correction(Q, Ri) = 100\% \text{ semDist}(Q, Ri) / \text{semDist}(Q, Top)$$

Results for the case study are:

$$Correction(Q, R1) = 58.8\%$$

$$Correction(Q, R2) = 100\%$$

Performance evaluations executed on an HTC-Google Nexus 9 tablet (equipped Nvidia Tegra K1 system-on-chip with 2.3 GHz dual-core CPU and 2 GB LPDDR3 RAM) demonstrate the feasibility of the proposed approach with resource-constrained devices. Results reported in Table III average ten runs: each run loaded the KB and matched three test descriptions – referred to different subjects and conditions – against each of the seven test outcome templates. Loading the KB required 134ms on average, but this is needed only once in the lifetime of the application. Matchmaking required less than 1.5ms on average for every request, and less than 2.5ms in the worst case.

IV. CONCLUSION

The paper presented a novel m-Health system for neuro-cognitive impairment monitoring based on P300 spatio-temporal characterization. The architecture exploits a new method for P300 characterization (t-RIDE) supported by a BCI

aiming to increase the cognitive rehabilitation contribution. t-RIDE-based diagnostic tool presented in [12] has been improved here by including a ML-based classification and a semantic reasoning that allows to adapt the t-RIDE outcomes to the test environment and filter the disturbance of a not standardized scenario. The BCI uses the presence/lacking of P300 to quantify the cognitive level of a patient and provides a feedback through the game, which adapts itself dynamically following the performance of the subject. The BCI classification reaches 86.8% of accuracy with a ML algorithm including only 38 target response patterns, and provides a decision in 2.4ms.

The system has been validated on a dataset of 12 subjects performing the game. The results identify a P300 degradation during the game (amp. 0.21 μ V/LVL, lat. 16ms/LVL) according with meta-analysis [18]. An early clinical assessment of m-Health has been obtained presenting it to specialized neurologists. The interviews most of all indicated the need of improvements in term of stability and comfort of the electrodes detection subsystem.

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