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Fuzzy Adaptive Cognitive Stimulation Therapy Generation for Alzheimer's Sufferers: Towards a Pervasive Dementia Care Monitoring Platform

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Abstract

In this paper, we present a novel system for cognitive stimulation therapy to progressively assess cognitive impairment and emotional well-being of dementia patients in social care settings. The system assesses patients interactions and computes performance scores for different areas of cognitive stimulation. Patient interactions are initially classified into predefined performance categories through clustering of a sampled population. New personalised stimulation plans tailored to match the patient's changing level of impairment are generated automatically through a set of fuzzy rule based systems using quantitative attributes and the overall scores of patients interactions. Therapists can redefine, evaluate and adjust the rules governing difficulty and activity levels for different stimulation areas to fine tune generated activity plans. The system can also be combined with an Internet of Things (IoT) enabled patient dialogue system for determining the affective state of participants during therapy sessions that could be used as a pervasive condition monitoring platform. Experiments consisting of therapy sessions of patients interacting with the

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system were performed in which the activity plans were automatically generated. Initial results showed that the system outputs were in agreement with the therapists own assessment in most of the stimulation areas. Simulation experiments were also conducted to analyse the system performance over multiple sessions. The results suggest that the system is able to adapt therapy plans overtime in response to changing levels of impairment/performance while supporting therapists to tune and evaluate therapy plans more effectively.

Keywords: Fuzzy System, Computer Assisted Therapy, Cognitive Impairment, Clustering

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1. Introduction

One of the major public health challenges in which IoT and smart medical systems can assist is Alzheimer's disease which affects a predominantly ageing population. Treatments for this disease require novel interactive and unobtrusive ways of both tracking disease progression and monitoring, emotional health and safety while accounting for the changing care needs of sufferers. Alzheimer's Disease International estimates that the number of people living with dementia worldwide is estimated at 46.8 million and this number will reach 131.5 million in 2050 [24]. The global cost of dementia is estimated at US $ 818 billion, and this is set to rise to $ 1 trillion by 2018 in part as a result of an ageing population brought about as a result of improvements in healthcare enabling more people to live longer [24].

Despite the lack of a cure for Alzheimer's disease, non-pharmacological therapies are often used (cognitive stimulation being one of the most advised therapies [37, 33]) with the goal of maintaining cognitive function or helping the brain compensate for impairments in addition to improving quality of life or reducing behavioural symptoms [2]. In this sense, Computer-Assisted Cognitive Therapy (CACT) systems have been found to be valuable tools for the delivery of often low cost and effective interventions with a number of associated benefits such as: inducing cognitive enhancement in older adults (60 to 85 years old) [1] and Alzheimer sufferers [31]; achieving more robust effects in reducing measures of cognitive distortion besides requiring reduced contact with therapists when compared to Standard Cognitive Therapy [38]; monitoring older adults and detecting early signs of frailty [40]; detecting sustained changes in cognitive performance [10].

In this paper, we present an adaptive system for cognitive stimulation therapy that analyses the performance of dementia sufferers during their interactions with computer-based activities to generate personalised stimulation therapies according to the sufferers changing levels of cognitive impairment. The aim of the system is to reduce the cognitive burden on care workers and therapists of supervision, monitoring, assessment and adaptation of therapy plans by delegating these functions to an intelligent system and enabling therapies to be performed at home via a mobile health computing infrastructure. These developments were integrated into an existing CACT software called Mente Activa for the treatment of older adults with cognitive impairment. The developed system makes use of Fuzzy Logic Systems (hereinafter, FLSs) for handling qualitative concepts (e.g., representation of abstract terms such as "easy", "difficult", "good performance", etc.), which can be used to describe the performance categories and characteristics of participants based on their interactions with the stimulation activities.

We present unique experiments based on Alzheimer sufferers' interactions with Mente Activa while attending a day care centre. The experiments are used to evaluate the plan recommendations determined by the fuzzy system against therapists' own assessments of recommended therapy for individual sufferers. Simulations of the system with data of different patients and cognitive areas are also carried out to demonstrate its ability to automatically propose an initial plan according to their mental health condition and adjust the subsequent generated therapy plans over time in response to user performance. As a means for assessing the emotional state of the sufferers, we report on the piloting of an IoT enabled patient dialogue system (using IBM's TJBot) with preliminary results on affect recognition analysis in the context of a targeted therapy session. We show how the proposed adaptive cognitive stimulation system can be integrated with the patient dialogue system and affect recognition system to enhance the system. This enhancement is achieved by processing context relevant quantitative and qualitative data streams including behaviour and affect data in the cloud using IBM Watson services.

The rest of this paper is organized as follows: Section 2 discusses current Computer-Assisted Cognitive Therapy approaches; Section 3 describes the software Mente Activa and techniques used in developing the proposed support system; Section 4 describes the developed intelligent performance assessment and plan recommendation system. Section 5 describes the integration of the IoT enabled patient dialogue system with initial experiments on detecting affective states of participants interacting with the Mente Activa software during a simulated therapy session. Evaluations of the developed system on participating individuals with dementia and simulated sessions are presented in Section 6. Finally concluding remarks and future work are discussed in Section 7.

2. Literature Review

Several approaches for CACT have been shown to provide effective intervention for older adults with dementia to improve their cognitive functioning as well as quality of life [40, 10, 25]. A study by Tarraga et. al. [31] performed 12 weeks of cognitive stimulation using an interactive multimedia internet based system (IMIS) treatment on a group of patients affected by Alzheimers. The results showed an improvement in their condition (measured using the Alzheimer's Disease Assessment Scale-Cognitive and Mini Mental State Examination), which was maintained through 24 weeks of follow-up sessions as compared to two other groups receiving only an integrated psycho-stimulation program and a stable treatment with cholinesterase inhibitors. A commercial initiative by [7] performed a controlled pilot trial of computerised cognitive training in older adults with mild cognitive impairment (MCI) also showed that participants were able to improve their performance across a range of tasks with training. In [14], a CACT program was assessed for fostering patients verbal engagement on previously selected life experiences/topics. In [21] a framework was developed which focused on validating the appropriateness of a prototype cognitive stimulation system for the elderly in terms of *usefulness*, *ease of use*, *user experience* and *intention of use* perceptions of the users. CACT have also been used to provide cognitive training monitoring older adults to detect early signs of frailty [40], and inferring a user's cognitive performance to identify significant performance changes as discussed in [10]. Lee et.al. [15] reported on the evaluation of a learning-based memory training program for persons with early Alzheimer's disease, finding positive effects on cognitive function. An online word training programme at home is presented in [27] as a therapy for Semantic Dementia sufferers achieving clear gains on picture naming.

Current research suggests that the early detection of cognitive decline has an important role in effective clinical intervention and the detection of imminent functional impairment [24, 34]. In order to facilitate effective clinical intervention, there is a need to gather and analyse data related to patients' performance during stimulation activities for physicians and care staff to easily interpret and make informed decisions related to disease progression and its implication on the patients treatment. The success of these forms of therapy relies heavily on the consistency of delivery (where each session could typically be for around 45 minutes undertaken at least twice a week [36]), requiring constant participation from the therapists. Due to this, there is a high cognitive load/burden of time and effort required from the therapists' in therapy planning and adjustment of activities to suite patient conditions.

None of the existing systems found in the literature provide support to the specialist in providing an interpretable way of analysing stimulation therapies and their effectiveness on the patient. These systems also do not handle the subjectivity and uncertainties associated with the evaluation of patients based on therapy performance, levels of difficulty and time spent during the assessment of different cognitive areas. Finally, these systems do not provide an integrated stimulation therapy and monitoring platform that is capable of self-adjusting therapy planes based on evaluating patient performance data and reducing therapist input for manually specifying therapies over time. These limitations make constant participation of therapists necessary in order to supervise the therapy intervention, assess patients' cognitive abilities while considering context and prior background details as well as keeping patients engaged with the activities while manually and subjectively adjusting therapy features such as difficulty, type and amount of activities, etc. The increased cognitive burden on the therapists to monitor these aspects may lead to possible inconsistencies in the way combinations and levels of activity are adjusted resulting in less effective therapy. There is therefore, a need to develop a therapy delivery platform which is unobtrusive, easy to use, practical and able to provide automated approaches for assessing, designing, delivering and adapting therapies in response to sufferers' cognitive performance and changing level of impairment.

While the cognitive condition information obtained in therapy is important to measure sufferers' progress, their emotion changes throughout the day must be considered as part of such therapy since such behavioural and emotional changes are often associated to Alzheimer symptoms [24]. The growing number of embedded and network-enabled physical devices collectively termed as the Internet of Things (IoT) has become an enabler for facilitating richer context awareness, personalization through integration of information sharing and connectivity [39, 20]. This influx of personal, mobile and wearable devices is set to revolutionize e- and m-health systems by bringing pervasive personalised real-time health informatics to consumers as well as enhancing existing dedicated clinical, biomedical and therapy based healthcare systems [9]. Contextually available data (e.g., wearable sensors, physiological indicators, affective states) can therefore be used to enrich cognitive monitoring systems to provide more patient-centred therapy and care planning decision support [13, 35].

3. Technology Foundations

3.1. Mente Activa

Mente Activa is an interactive software developed as a result of a collaboration between the Instituto Tecnológico de León and the Institute of Memory (hereinafter ITL and IM respectively) aimed to provide Computer-Assisted Cognitive Therapy. This software is based on using auditory and visual stimuli prompting different cognitive functions (based on [12], [31] and [28]). More specifically, the software allows cognitive stimulation through the use of interactive games designed by psychologists, running on computers with touch screen and multimedia elements such as audio instructions and interactive images. In Fig. 1, seven examples of activities corresponding to the seven areas of stimulation are being shown. For further details on the activities see [22].

3.1.1. Cognitive Stimulation Activities used in Mente Activa

The activities are divided mainly by types of cognitive stimulation [29, 6] based on seven key areas. For a brief description see Table 1.

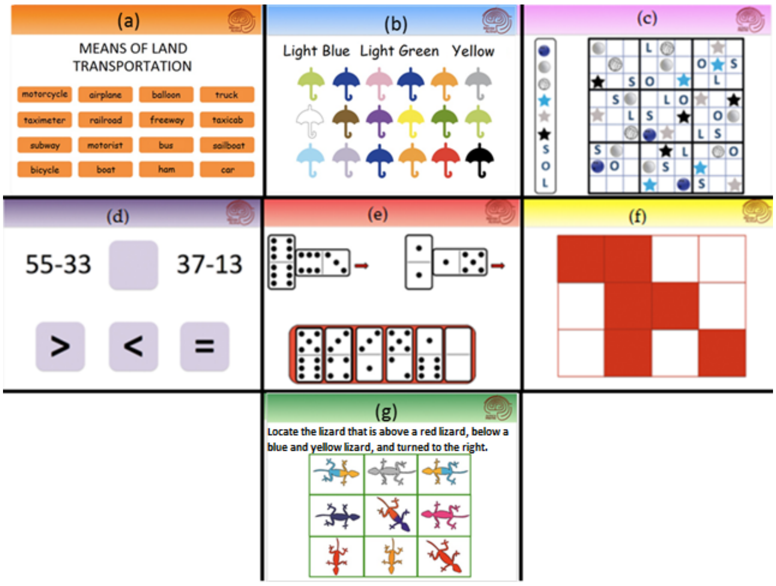


Figure 1: Some activities of Mente Activa: (a) language, (b) gnosias, (c) executive functions, (d) calculus, (e) attention, (f) memory and (g) orientation.

Table 1: Fields of cognitive stimulation

Field	Definition
Attention	It is a function under which a stimulus or object is in the focus of consciousness, distinguished from the rest accurately by displacement, attenuation or inhibition of irrelevant stimuli.
Memory	The faculty of the brain that allows recording new experiences, and remember past events.
Language	It is a code of sounds and graphics that are used for social communication among humans.
Gnosias	Knowledge gained through the elaboration of sensory experiences.
Executive Functions	Defined as the processes that associate ideas, movements and simple actions aimed to solve complex behaviours.
Calculus	It involves aspects of basic mathematical concepts, cognitive development, operational performance, reasoning, deduction and perception skills.
Orientation	It is the ability to establish relationships between events and objects in space.

3.1.2. Therapist's judgement based Computer Assisted Therapy

The purpose of this computer based therapy is to adapt the stimulation activities to keep them being sufficiently challenging (keep the user engaged with the therapy) while considering the patients' cognitive abilities which may be changing due to how their disease is progressing. In order to achieve this, the IM employs a team of psychologists who commonly treat a limited group of people due to the thoroughness required which demands a substantial effort from the therapists for several reasons:

- Each stimulation plan must be customized to the patients' conditions and cognitive decline in a medium-long term.
- The patients' performance might be monitored and assessed by different therapists and therefore, patients' performance evaluation is subject to subjective perceptions. In addition, there is a number of potential issues implied that influence the evaluation (e.g., changes in therapists staff with different experience, patients' mood, etc).
- Taking into account the last performance and/or current conditions, the therapists must propose further stimulation plans selecting individual exercises for each activity based on their experience. This also implies that they must be able to remember a wide variety of dynamics across the whole set of stimulation activities.

Such level of engagement required from the psychologists makes it difficult to work with large groups of patients at once, which limits the number of people receiving this treatment.

3.2. K-Means Clustering

K-Means [16] is a well known unsupervised learning algorithm which creates k hard partitions of data observations based on locations and distance between the input data. The algorithm requires the selection of k points representing initial cluster centroids into the space. Posteriorly, each datum is assigned to the cluster that has the closest centroid and, when all datums have been assigned, the k cluster centroids are updated using the new data assignations. This allocation and recalculation is iteratively repeated until there is no changes in centroids/assignations of data observations.

3.3. Fuzzy Logic Systems

Fuzzy Logic Systems (FLSs) can be considered as systems able to provide non-linear mapping of input data to an output. They are widely used as rule induction based approaches for extracting information in the form of IF-THEN rules from experts. FLSs have the capability of handling subjective and uncertain knowledge [19] by accounting them with Fuzzy Sets defined by Membership Functions.

Rule based FLSs perform four processes: (1) in a first stage, the *fuzzifier* maps crisp input values into input fuzzy sets (FSs) representing the input variables. (2) Rules associating linguistic input variables (represented by FSs) to a linguistic output variable (represented by output FSs) are activated. The Rules are expressed as a collection of IF-THEN statements and may be provided by experts or can be extracted from numerical data [4, 5, 11]. (3) The inference engine maps input FSs into output FSs by handling the way in which the rules are activated and combined to generated an aggregated output FS which is converted (4) to a crisp value by the Output processor through a process of *defuzzification*.

Both K-Means and FLSs represent the main components of the proposed support system used to learn from patients interactions and represent/use therapists knowledge. The next section covers implementation details of our developed system.

4. Proposed Therapy Evaluation and Adaptation System

In section 3.1, we have described a CACT tool used for cognitive stimulation therapy which comprises a wide variety of activities of different cognitive areas and difficulty. In its current form, this therapy requires constant supervision from a therapist to assess the users' interactions with the system and suitably adapt the type and difficulty level of activities based on her/his own experience and knowledge. Due to the reasons mentioned in section 3.1.2, there is a need for an auto-adaptive therapy delivery and assessment system able of monitor the user interactions on behalf of the therapist. To achieve this, two main aspects are considered: (1) patient-software interactions classification must be performed in order to assess their performance on completed activities (e.g., good, bad, etc), (2) an interpretable and adaptable representation of the stimulation plans incorporating the knowledge normally held by therapists needs to be designed.

Consultation with therapists at the IM regarding their practical experience and the involved dynamics on therapy evaluation determined that patients' performance can be assessed by recording the time required to complete an activity, achievement of objectives and frequency of incorrect responses. Furthermore, circumstantial characteristics which also have influence on individuals' performance (e.g., years of education, cognitive status) have been proposed. Together, these combined characteristics can be used to provide more comprehensive performance data enabling a better generalization and determination of recommended courses of therapy. For these reasons, we propose a model considering several aspects. We combine in a tuple $r = (e, t)$ two main characteristics during the interactions of users with the stimulation software to represent the performance, namely: e for the number of errors per activity, and t representing the time required to complete each activity. All data considered by the system and its relevance to the creation of the stimulation plans are summarised in Table 2, while the notation used to describe all elements in the system is provided in Table 3.

Table 2: Data considered in the IM for the design of stimulation plans.

Data	Rationale	Measurement Frequency
Mini Mental (MM) Test Score	With this score [8] the user's impairment can be categorized into one or two cognitive states (i.e., indicating a possible course of cognitive changes over time) according to the GDS scale [26].	Twice per year
Years of education	People with fewer years of formal education are at higher risk for Alzheimer's and other forms of dementia than those with more years of formal education [30]. Since there is a positive correlation between years of schooling and cognitive status we have considered this data as an input for the system.	Once
Performance per area	It is defined based on the scoring over all activities performed for a given stimulation area by using a scoring function (see (5)). It uses the number of errors and the time required to complete each activity.	Every session
Difficulty	Given that the user performance should be evaluated according to the level of difficulty set during a given simulation session.	Every session
Neuropsi Punctuation	This test [23] is a more comprehensive measure of cognitive status than MM, although the categories referred to depend heavily on schooling and age.	Twice per year

Considering that the data used to represent the performance r can be obtained directly through the Mente Activa system, a learning approach is used to evaluate the performance categories (e.g., good or bad performances) in a similar fashion as a therapist would describe them linguistically. This approach is described in the next subsection.

Table 3: Notations used throughout this paper

Notation	Meaning
c	an item $c \in k$
g	a cluster centroid
r	a tuple $r = (e, t)$ of errors and time for an specific activity
m	an item $m \in N$ associated to an activity
N	the total number of interactions with an activity
r_0	a tuple $r = (0, 0)$
φ	the allocation function
v	a cognitive area $v = \{a, ca, ef, g, l, me, o\}$
n	the number of completed activities in a patient interaction
p^v	the performance score in the v area
A	the set of all activities $act_s \in A$
s	an item $s \in \|A\|$
act_s	an activity with a *name*, *area*, *level* and N associated
SP_j	an stimulation plan in the j session
FLS_j^v	a FLS for the v area and j session
u	a patient $u \in U$
L	a list of activities $L \subset A$
R^v	the set of tuples for activities performed in current SP_j
d_j^v	the average difficulty level of a set L^v
D^v	the tuple of recommended features for an SP: difficulty and amount

4.1. User Performance Modelling

Given a number of performance records $m = 1, ..., N$ of interactions with an activity from patients with different diagnosis, we need to obtain $k = 3$ cluster centroids which will be used subsequently to classify further interactions in an unsupervised manner. In our developed system, K-Means clustering is used as we want to initially provide crisp partitions of the input space (a datum r is assigned to a single cluster). We initialize the cluster centroids $g_c, c = 1...k$ using a distance-based criteria which allow us to clearly differentiate each cluster (initially with considerable separation) defining our performance categories in the feature space. The initial centroids are chosen as follows:

- Selecting the point with a feature vector having the nearest distance $d(r, r_0)$ to the origin of our feature space ($r_0 = (0, 0)$ i.e., 0 errors and 0 time in minutes) based on the Euclidean distance metric. The cluster formed from this initial centroid will have an association with a good performance given that, less errors are committed and less time is required to perform an activity (see 1).

$$g_0 = r_m \quad | \min_{m \in \{1,\ldots,N\}} ||r_m, r_0|| \tag{1}$$

- Selecting the pattern with a feature vector having the highest distance to the origin. The cluster formed from this initial centroid will have an association with a poor performance (see 2).

$$g_2 = r_m \quad | \max_{m \in \{1,\ldots,N\}} ||r_m, r_0|| \tag{2}$$

- In the case of regular or average performance, the feature vector with the median performance $d(r, r_0)$ over all patterns for a given activity and difficulty level is selected as then initial cluster centroid (see 3).

$$g_1 = r_m \quad | \quad median_{m \in \{1,\ldots,N\}} ||r_m, r_0||, \tag{3}$$

  where $\|r_m, r_0\|$ is a distance function.

The rationale of "grouping" the records in this way is to allow the system to differentiate between 3 meaningful performance categories based on the assumption that the less errors committed and the less time needed to complete the activity, the better the performance. The clustering process is applied to collected data representing different interactions with the simulation activities from a population of patients. From this process we obtain $k = 3$ cluster centroids (per activity) which will be used to classify in an unsupervised manner future performance vectors r_m related to that activity (see (4)). The allocation (represented with the function $\varphi(r)$) is performed by assigning each datum r_i to the nearest cluster centroid (based on the Euclidean Distance) where each centroid is related to a numeric performance category (label) 0, 1, and 2 for 'good', 'average' and 'bad' respectively. Note that for this step, it is necessary to have a minimum number of interactions beforehand (we used 20 as minimum in experiments) in order to form the initial clusters.

$$\varphi(r) = \begin{cases} 0 & argmin_{c=1,\ldots,k} = \|r, g_0\| \\ 1 & argmin_{c=1,\ldots,k} = \|r, g_1\| \\ 2 & argmin_{c=1,\ldots,k} = \|r, g_2\| \end{cases} \tag{4}$$

In the next section we explain how we convert the categorically assigned performance scores obtained using the allocation function $\varphi(r)$ for all the completed activities r to an overall performance score for each cognitive stimulation area.

4.2. Evaluation of user performance

Given a cognitive area v, the evaluation of user performance is made separately by summing each labelled instance of performance data generated in (4) for each of the n completed activities undertaken as part of current session with the system. The sum of these scores is subsequently mapped from a range of 0 to $2n$ to a normalised range between 0 and 10, since the number of activities per area in each session can vary. This mapping is calculated as follows:

$$p^v = 10\left(\frac{2n^v - \sum_{i=1}^{n^v} \varphi(r_i)}{2n^v}\right), \tag{5}$$

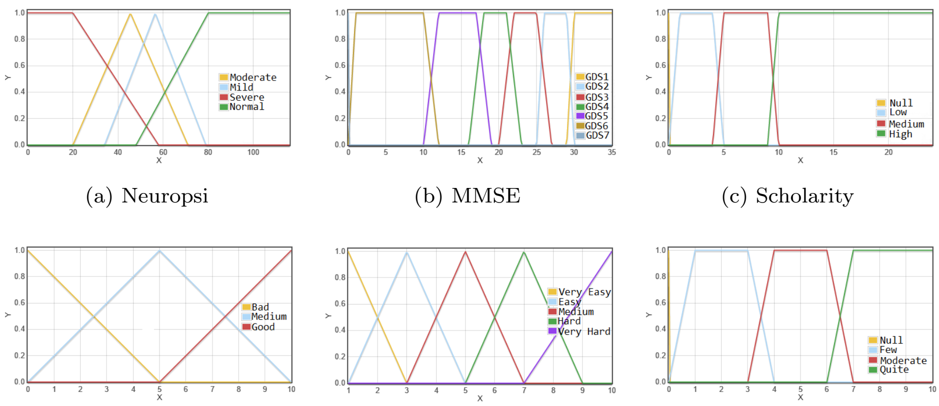
where n^v is the number of completed activities in the current stimulation area $v \in \{a, ca, ef, g, l, me, o\}$, $\varphi(r_i)$ is the score (numeric labels) obtained from the allocation function (4) and p^v is the overall performance for the vth stimulation area. The calculated final evaluation values are used as crisp inputs (not rounded to integer) to the therapy recommendation system for each of the seven cognitive areas assessed by Mente Activa.

4.3. Therapy recommendation and adaptation system

In our application context, there are different sources of uncertainties involved in the formulation of stimulation plans (e.g., imprecise and subjective assessments of the patients performances, their level of cognitive impairment and perception of activities difficulty by the therapists) which can increase as the user completes stimulation activities over time and is affected by their progressive condition. Therefore, the therapy recommendation system must be able to automate the design of stimulation plans while dealing with such sources of uncertainty. In the next subsections our proposed approach of therapy recommendation system is described.

4.3.1. Implementation of FLSs

A MIMO (Multiple input, multiple output) FLS is the core of the system, using: Mamdani inference [17], singleton fuzzification and centroid defuzzification. In order to design the Membership Functions (MFs) and the initial set of rules for each FLS we consider the current knowledge related to mental health diagnosis together with a close consultation with staff at the IM. From this process, an intuitive set of linguistic quantifiers (fuzzy sets) was derived for each of the input parameters being considered. The design of these was based on subjective measurements, knowledge and experience of the therapists and physicians who were consulted.



(a) Neuropsi (b) MMSE (c) Scholarity

(d) Performance (e) Difficulty (f) Amount

Figure 2: Membership Functions for linguistic variables used in the FLSs.

- ***Neuropsi* input value**. Neuropsi comprises of several age groups and years of education. We focused on the range listed for ages of 66 to 85 years (see Fig. 2a)..

- ***MMSE* input value**. Mini Mental State Examination [8] is assessed and classified into 7 Geriatric Depression Scale (GDS) states. For our purposes, the ranges from [26] were taken as basis for the trapezoid MFs (see Fig. 2b).

- ***Scholarity* input value**. Since clinical assessments consider a person might have an "expected performance" according to their years of schooling, we used the age ranges proposed in Neuropsi [23] to represent different levels of education by using trapezoid MFs (see Fig. 2c).

- ***Performance* input value**. A range from 0 to 10 was chosen to ease the psychologists' interpretation of this variable. The MFs were chosen to be equidistant and symmetrical triangular fuzzy sets in accordance with IM psychologist's criteria (see Fig. 2d). Three fuzzy sets for *Bad Performance*, *Medium Performance* and *Good Performance* were defined. These fuzzy sets are related to the performance categories used in the unsupervised classification process described in section 4.2.

- ***Difficulty* input/output value**. The *difficulty* input parameter uses a range from 1 to 10, as activities difficulty is defined over this range. MFs were chosen to be equidistant, symmetrical and overlapped triangular fuzzy sets in accordance to IM psychologists criteria (see Fig. 2e).

- ***Amount* output value**. Often, the therapists may recommend to interact with some stimulation areas to a greater or lesser extent. This can be achieved with a FLS by adjusting the number of activities suggested per area. Therefore, four overlapping fuzzy sets were used to represent the activities' *amount* parameter through trapezoid MFs (see Fig. 2f). The parameters were based on a range from 0 to 10 as follows: *null amount*, *few amount*, *moderate amount* and *quite amount*.

4.3.2. Generation of Initial Stimulation Plan

Following the registration of a new patient, parameters about the patient condition are entered into the system, namely: years of schooling, age, clinical diagnosis, scores based on Mini Mental and Neuropsi tests and medication. That information is used by the system through a set of dedicated FLSs for each of the seven assessed cognitive areas in order to generate an initial stimulation plan SP_0. Considering that in a first instance, there is no information related to performance and difficulty available, the FLSs rules are initially only related to the inputs MM, Neuropsi and

Schooling. More formally, the generation of the initial stimulation plans relating to the different cognitive area specific FLSs can be described as follows:

Let L be a combined lists of activities, where $L \subset A$ (recall symbols from Table 3), we need to associate the initial stimulation plan from session $j = 0$ represented as $SP_0 = (u, L)$ to a patient u such that every L_j^v (see (6)) is proposed as a result of the D^v outputs by the different FLSs.

$$L = L_0^a \cup L_0^{ca} \cup ... \cup L_0^o \tag{6}$$

Such lists L_j^v are generated by selecting activities which together, have similar or equal characteristics to the suggested D^v outputs of the FLS_0^v. The outputs are tuples $D^v = (l^v, a^v)$ representing the l^v average difficulty and a^v activity amount characteristics in a cognitive area v. Hence each FLS_0^v recommends if the given cognitive area needs to be worked on based on the amount of activities and also their average level of difficulty. An example of the rules used in the system for a given cognitive area is:

- *R1: IF Scholarity is High AND Neuropsi is Moderate AND GDS-5 THEN Level is Medium*

4.3.3. Consequent Stimulation Plans

Once a user has completed one stimulation plan SP_j, the next plan SP_{j+1} can be generated by taking into consideration the overall interaction data represented by R^v and average difficulty d_j^v per cognitive area as is shown in Fig. 3. Note that R^v represents only exercises that were completed:

$$R^v = \{r^v | r^v \neq r_0\} \tag{7}$$

As can be seen, the initial process depicted in Fig. 3 is being referred to here as the *Initial SP Generation* process. From that point, the system then, performs the following steps in order to generate subsequent stimulation plan as follows:

1. Once a user has interacted with a stimulation plan SP_j, we use R^v and d_j^v to represent the interaction data which the system proceeds to analyse.
2. Each cognitive area v is evaluated by using (4) and (5). This evaluation generates a number of scalars p^v representing the performance score in the v area.

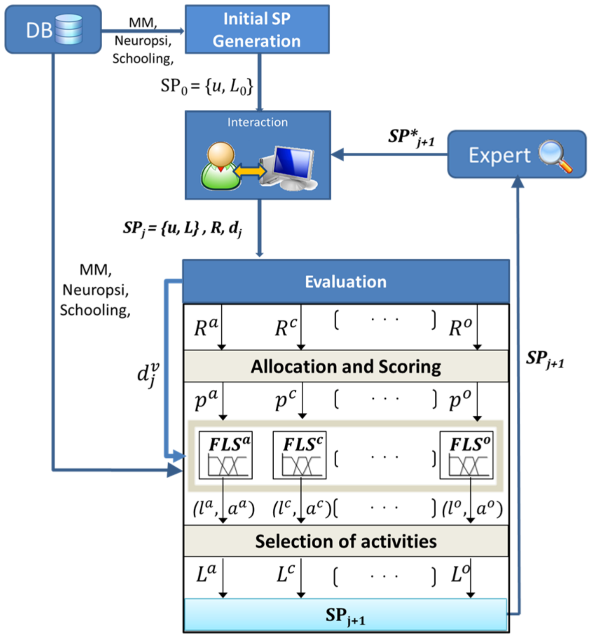


Figure 3: Structure of the system

3. Based on the data described on Table 2, the p^v performance scores, the average level of difficulty per area d_j^v, and user information (years of school, Neuropsi and Mini Mental scores) are used as crisp inputs for the different FLS_j^v.

4. The FLSs generate the recommended *difficulty* and *amount* of activities per area as crisp outputs (l^v and a^v).

5. In the *Selection of activities* process, the FLSs outputs are used to select automatically a number of activities which approximate the required features by choosing the nearest integer value for the amount of activities and, the average difficulty for the set of activities in a each stimulation area. These selections generate the lists of activities L^v, which together, generate a new stimulation plan SP_{j+1}.

6. The plan SP_{j+1} can either be available to be directly performed by the patient or analysed and adapted by the therapist to generate a modified version of the new stimulation plan SP^*_{j+1}.

Note that step 2, implies using the previously created cluster centroids which must be periodically refined through re applying K-Means algorithm as new user interaction data is collected (this function is currently embedded in the software system). Also, note that the patient information used in each FLS (e.g., Mini Mental score) can be periodically revised based on routine medical assessments. In addition, therapists can revise therapy plans by modifying the set of rules for each FLS FLS_p^v based on their expert knowledge and assessment of the user. The system allows the premises and consequents of the rules to be modified by a specialist using an intuitive interface.

5. Integration of IoT enabled Patient Dialogue and Affect Recognition

Our proposed integrated architecture is formed by different components arranged in the following layered structure. The first layer is the *user* layer, who can be a patient or a therapist that interacts with the system either on-site or remotely from home (signified as the second layer). The third layer comprises of the *physical devices*, that the users are able to interact with. Here two components are considered: the computer running Mente Activa software, and TJBot as a means for voice interaction with the user. The fourth layer contains the *data components*, namely: the Mente Activa database (saving the information collected by the software) and IBM's servers (receiving the information from the TJBot and linking it to the IBM Watson sentiment analysis service). The fifth layer consists of the *application components*: Mente Activa (software running the cognitive games) and IBM Watson. The sixth and final layer contains the *processes*: intelligent methods to generate customized stimulation plans as well as IBM Watson services.

IBM Watson uses linguistic analysis to detect emotional language (anger, fear, joy, sadness) and language tone (analytical, confident and tentative) found in the dialogue with the user[2].

In order to evaluate IBM Watson as a tool for monitoring patients emotions throughout the therapy, we performed initial tests with five different users at different points of interaction with the system. In table 4, we show the dominant emotional and tone scores obtained from common expressions in the dementia care scenario, where a score close to 1.0 indicates a high possibility of the emotion/tone presence.

[2]For further details, check `https://console.bluemix.net/docs/services/tone-analyzer/using-tone.html`

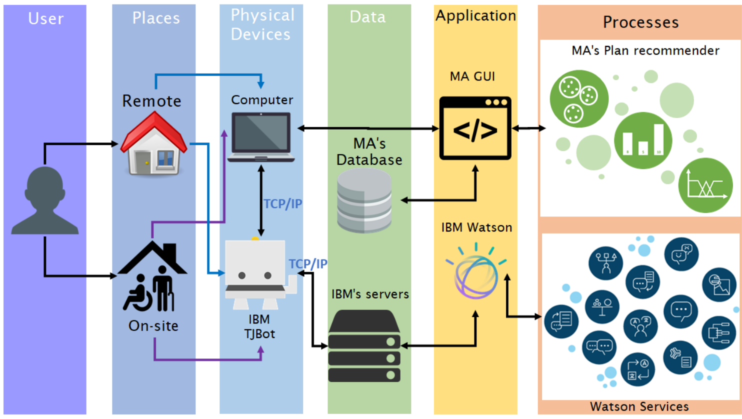


Figure 4: Block diagram showing communication among the different components.

Table 4: Initial test showing a short dialogue from the user, and the emotions detected.

Dialogue	Emotional	Tone
Today I don't feel very well. I am tired.	Sadness: 0.71	Analytical: 0.93
Good morning. Today is very sunny.	Joy: 0.90	Confident: 0.99
I didn't sleep very well.	-	Confident: 0.94
I like this game, is very funny and entertaining.	Joy: 0.70	Confident: 0.66
When I don't get the answer right, I feel disappointed.	Sadness: 0.79	Analytical: 0.86

As can be seen from Table 4, emotional and tone scores obtained seem to be consistent with the verbal expressions. These findings, while preliminary, suggests that we can integrate emotional information into the therapy recommendation system which will allow us to have a more comprehensive model and therefore, generate stimulation plans more in line with the real needs of the user. Hence the patients can interact with the system (TJBot and Mente Activa), generating information regarding both their performance during therapy sessions and the emotions detected by IBM Watson (see Fig. 4). This interaction can be given through a chat or voice dialogue available at specific moments of the stimulation exercises. Moreover, the TJBot aesthetically appeals to patients due to its small form factor and engaging appearance as part of proposed stimulation therapy system (see Fig. 5).

Figure 5: TJBot integrated within the therapy environment for IoT connected dialogue.

6. Experts-based Evaluation of Mente Activa

In this section, we show the results of using this approach as a tool for dementia therapy support. We focus on different aspects: (1) analysing the changes in users' responses over a number of sessions using the Mente Activa software (Section 6.2); and (2) the practicality for modifying the system through the rule base between sessions with patients, showing how stimulation plans are generated and therapy features change over these sessions (Section 6.3). Lastly, we present a series of simulation results focusing on analysing the consequent changes on therapy features over multiple sessions through different plan generations in response to changing user interactions (in Section 6.4).

6.1. Collection of initial data

Before creating models for unsupervised performance classification, there was a data collection process which involved recording all patients' interactions during 3 months in the IM. During that time frame the therapists manually designed the stimulation plans for 39 patients diagnosed with mild cognitive impairment and early stages of dementia.

The patients all consented to participate in 1 to 2 sessions per week in which they interacted with the Menta Activa software for approximately 45 minutes per session and were excluded from further experiments. Data was collected on the time and number of errors of each activity pertaining to a specific cognitive area that a patient successfully completed during the sessions. The collected data was used to construct the cluster centroids related to different activities which were used to assess the performances of different areas (as described in 4.2).

6.2. Evaluating the Effect of Stimulation Plans on Patients

We are interested in a longitudinal study comparing a feature (performance) in a population before and after stimulation. Thus, we designed 7 stimulation plans in Mente Activa with the supervision of psychologists from the IM featuring a varied selection of activities in term of difficulty (levels 1, 5 and 8) and all cognitive areas. The 1st and 7th plan were designed with the same activities to be able to carry out the comparison of the participants performance related data from the initial and last sessions.

A series of therapy sessions were developed to deliver the plans to a population of dementia patients from a different Gerontology Center called DIF (standing for Desarrollo Integral de la Familia) to test if there were significant changes in user responses after one month. The subjects were eligible to take part if: (1) they were older than 60; (2) they had a low educational level (less than or equal 6 years of education); and (3) they had reported low/no experience with computers. The study was performed in accordance with approval granted by the IM, DIF and consent of all participants. We ran the sessions (limited to one hour per day) with 7 participants diagnosed with mild levels of dementia who completed their assigned activities in the time frame planned and agreed with the institution. Information from their interactions with the different stimulation plans was recorded and, performance of the first and last sessions was measured based on their errors and time required to finish each activity.

A Student T-test for paired samples was used to compare initial and last performance related measurements. Such a test requires a dependant variable to follow a normal distribution, hence, we analysed the Euclidean norm of both sets of data in advance with the Shapiro-Wilk test of normality. In both sets of data, we found performance significances of 0.551 and 0.993 for the initial and last stimulation sessions respectively. Therefore, given that both values are greater than the alpha level ($\alpha = 0.05$) it can be confirmed that both distributions are normal and we can proceed to use the dependent T-test for paired samples.

In Table 5 we show the average performance for all stimulation areas using the Euclidean norm so that the lower the value (less errors and less time required) the better performance. As can be seen by comparing the initial and last means, there is a considerable decrease in the number of errors and time spent when interacting with the activities presented in the first session. Though there is a need to conduct longer term future trials to measure and validate cognitive improvement as a result of the therapy, the observed differences do suggest a significant adaptation by the user to an unfamiliar therapy approach (CACT).

Table 5: Mean and standard deviation of performance per user shown in initial and last sessions

	Initial	Last
User 1	1.0573(±) 1.3789	0.8507 (±)1.2676
User 2	0.8905 (±) 1.2789	0.6519 (±) 0.8576
User 3	1.3937 (±) 1.5831	1.1090 (±) 1.4643
User 4	1.8689 (±) 2.3604	1.3952 (±) 2.3604
User 5	1.2566 (±) 1.7712	0.9502 (±) 1.6301
User 6	1.9806 (±) 2.5457	0.9995(±) 1.3950
User 7	2.1566 (±) 2.8269	1.2657 (±) 2.2780
Averages	**1.5149 (±) 0.4890**	**1.0317 (±)0.2509**

By using a confidence interval of 95% we obtained a p-value $= 0.007$ thus leading to conclude that there were significant differences in the overall performance of users following a plan of cognitive stimulation applied during a month in the Gerontology Center DIF León. One could argue that these results might be affected by the users having a biased advantage as they were presented with the same activity at the start and end sessions of the month. However the fact that the users performed several in-between activity sessions each spanning the seven cognitive areas, together with their initial unfamiliarity with the tool and level of impairment, would suggest that the system can be an appropriate tool for stimulating and exercising users cognition.

The length of the period (one month) of study was not long enough to allow us to test the patients' cognitive change, as clinical tests to show significant conclusions would require at least 6 months. However, this study has allowed us to: (1) measure an improvement on participants performance in interacting with the Mente Activa tool (as seen in Table 5); (2) encourage participants to use CACT as they reported that the system enhanced a sense of achievement; and (3) gather data on patients interactions with different activities for generating and updating the cluster models for unsupervised classification of performance.

6.3. Rule-base initial development and tuning

In order to perform an initial evaluation of the intelligent module in its ability to generate appropriate and effective stimulation plans for patients, it was necessary to create a set of rules through consultation with the IM specialists (based on their experience and knowledge). To test the system plan suggestions we convened a population of ten patients who had never interacted with the system before with moderate dementia. Two interactions within one week were authorized with the patients in which, the stimulation plans generated by the system (initial SP_0 and subsequent SP_1), were monitored by three IM psychologists in charge of leading these sessions with patients with this level of impairment.

After the first interaction in which only *MMSE*, *Neuropsi* and *Years of Education* were used to generate the initial SP_0. Subsequently, the intelligent module analysed the outputs from these first interactions (now taking into account the user *performance* and average *difficulty* per area) thus generating the subsequent features for the stimulation plan SP_1.

Considering that the developed system cannot be objectively validated with expected or desired results due to the lack of a specific objective function to be optimized, the evaluation of this system is largely based on comparing its performance with the judgement of experts that would otherwise be manually and directly designing the therapy plans. Therefore, we collected the opinions of the three psychologists who designed the rule-base and supervised the interventions in order to measure the extent to which they agreed with the features of the automatically generated stimulation plans. The opinions were based on their agreement with the proposed plans SP_0 and SP_1. For this purpose, we designed a Likert-based survey with a range from 1 to 5 (Strongly disagree to Strongly agree). The key aspects to evaluate were the difficulty and amount (per stimulation area) proposed by the system in relation to the users' condition and performance shown during the interactions. Thus, we made two questions per cognitive area with a rating scale based on the aggregation of 14 scores (i.e., 2 questions $\times 7$ areas).

According to the opinion of psychologists from the IM, average agreement varies considerably depending on the cognitive area in question. This is attributed to: (1) similar rulebases for most of the areas; and (2) there was a lack of standardization in the levels of difficulty, i.e. a difficulty n does not require the same mental effort in

Table 6: Averages of agreement towards system suggestions per are in a 5-point Likert scale for 10 patients

Area	**Difficulty**	**Amount**
Attention	3.89 (±0.93)	3.67 (1.00)
Calculus	4.33 (±0.87)	4.00 (±0.87)
Ex. Functions	3.40 (±1.14)	2.60 (±0.89)
Gnosias	4.63 (±0.74)	4.57 (±0.79)
Language	4.63 (±0.74)	4.00 (±0.93)
Memory	3.25 (±1.26)	3.50 (±0.58)
Orientation	4.02 (±0.60)	3.72 (±0.70)

all cognitive areas (e.g., *Executive Functions*, *Memory*, and *Orientation*) as some are inherently more complex than others, since they involve using several brain functions together to different extent. However, the stimulation plans proposed by the system can be manually improved by adding/removing individual activities which better approximate therapist's judgement. This was also reported as being useful for the therapists by assisting them in the adjustment of activities in a more consistent and time efficient way.

6.4. Simulation results

We acknowledge that the results shown for the developed therapy approach, in a real context are limited and a longer term trial is required to evaluate the approach's effectiveness (to be presented in a future publication). However, from a computational perspective we are still able to evaluate the performance of the system using simulated data to provide an insight into its functional capability when testing with practical limitations.

In order to develop the simulation experiments, we have used the information from the 7 patients who completed the 7 sessions and follow the process sequence depicted in Fig. 6. Firstly, we used the scored points in Mini Mental, Neuropsi and years of school to generate the first stimulation plan by using rules which do not consider *performance* and *level* as input data in the FLS_0. Following this, we used the patients interaction records from the first two sessions as a single session and performed bootstrapping (by sampling the difficulty d^v and interaction records R^v 1000 times per each v cognitive area) with each patient profile. Subsequently,

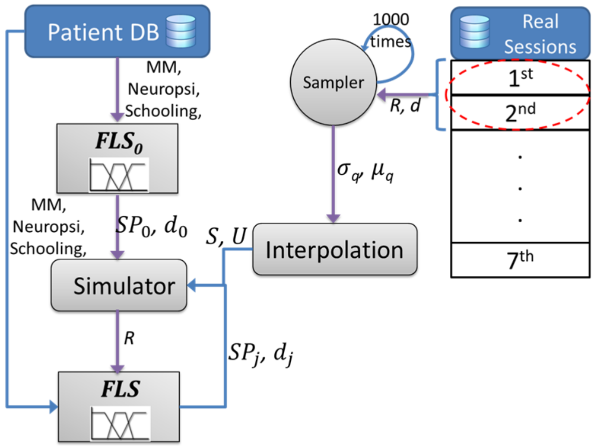


Figure 6: Process sequence for generating simulation results.

we generated statistical estimations (μ_q and σ_q where $q \in \{1, 5, 8\}$) related to the patients' initial performances. Given that the available data was related only to difficulty levels of 1, 5 and 8, we subsequently employed linear interpolation in order to estimate the statistics associated to missing levels, obtaining thus, two sets of statistics $S = \{\sigma_1, ..., \sigma_{10}\}$ and $U = \{\mu_1, ..., \mu_{10}\}$. These sets were used to generate simulated patients' responses based on statistics (represented by the *simulator* block in Fig. 6) over different levels and stimulation areas.

We then simulated 10 sessions by generating stimulation plans along with user responses. More specifically, we created a first plan SP_0 using only the initial information as described in section 4.3.2. The patients' interactions with this first stimulation plan were simulated from the statistics generated in bootstrapping which were used to generate subsequent interactions SP_1 to SP_9 and the activities in each plan were proposed by the FLS as described in Fig. 3. Due to space consideration in this paper, we focus our results on the areas of *Attention* and *Calculus*. In Figures 7 and 8, we show the recommended levels and performance obtained by the 7 simulated patients' interactions in each session for the *Attention* and *Calculus* areas. Note from the Figures that we are showing 9 simulated sessions because for the first interaction, there is no *performance* input and the recommended level is calculated by using other values (Neuropsi, GDS state and years of school).

As can be seen, for each change in simulated user performance there is a "slight" adjustment of the recommended level. It is worth noting that despite both these

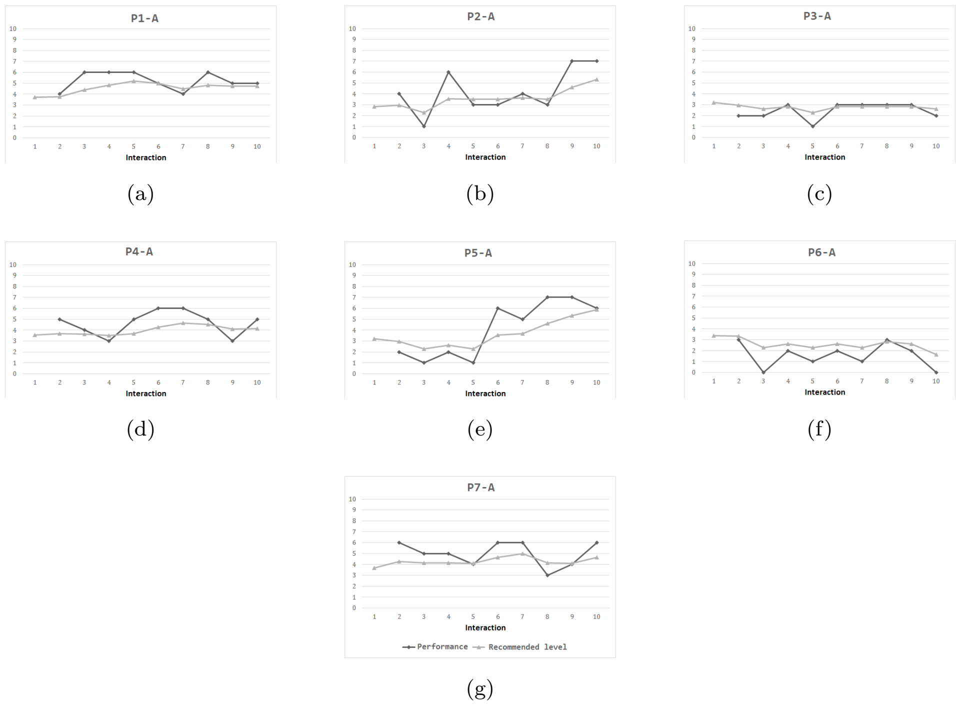
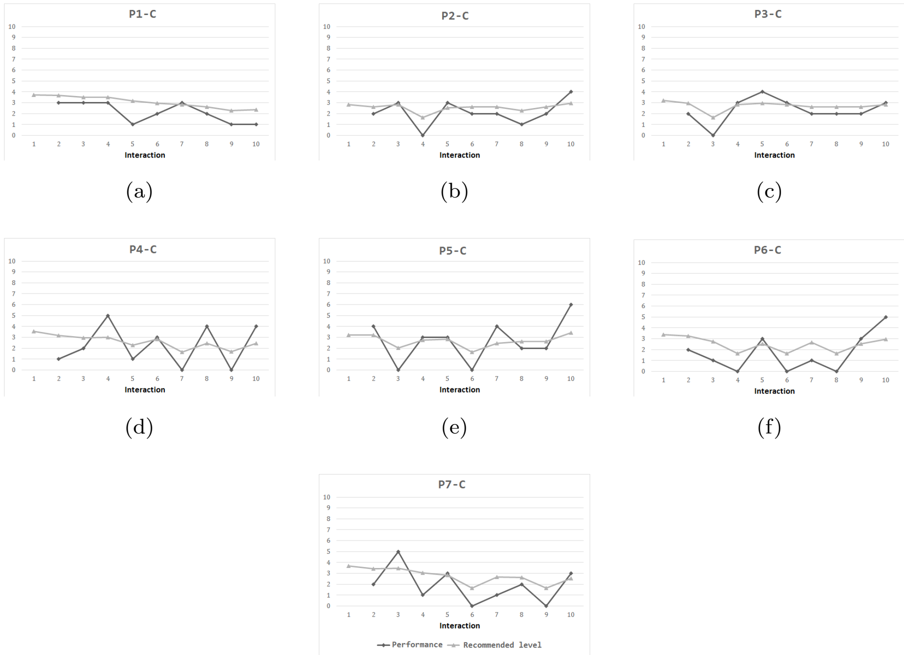


Figure 7: Simulated performances and consequent level recommendations from Fuzzy Logic based module for the Attention area. Dark grey and Light grey lines represent the performance and recommended level respectively.

values being shown in the same chart, both values represent different indices and it is not the aim of the FLSs to approximate the performance (i.e., difficulty $\neq$ performance) but to respond to performance changes according to experts' criteria while considering several other patients' characteristics. In other words, adjustments in recommended levels are partially correlated with the patients' performance, which implies that system responses are driven by patients' performance that has a bearing on their cognitive state. To further verify this, we calculated the correlation coefficients of the simulated patient's responses and difficulty recommendations using Pearson rank values and found a positive and significant correlation in all cases (see Table 7).

It is worth mentioning that, (1) the presented results come from rule-bases totally designed by experts and further tuning is needed; (2) the preliminary results obtained with this approach are useful to show the suitability of applying FLSs as an interpretable and flexible methodology to provide automated plan suggestions which



(a) (b) (c)

(d) (e) (f)

(g)

Figure 8: Simulated performances and consequent level recommendations from Fuzzy Logic based module for the Calculus area. Dark grey and Light grey lines represent the performance and recommended level respectively.

could be extended to use self adapting rule-base with rule generation, adaptation and removal; and (3), in order to develop a full care intervention with a self adapting rule-base an optimization approach with an evolving objective criteria should be adopted.

6.5. Comparative

From a different perspective, the proposed approach can be considered as an instance of a knowledge-based (KB) recommender system, in which personalized

Table 7: Correlations between estimated performance and recommended level of difficulty in 10 simulated interactions.

Patient	P1	P2	P3	P4	P5	P6	P7
corr_A	0.596	0.844	0.774	0.563	0.874	0.896	0.703
corr_C	0.721	0.897	0.867	0.558	0.896	0.693	0.713

information is used to automatically select a set of items (tasks) on behalf of a human according to a criteria (e.g., therapy suitability). Comparing conceptually KB systems against other popular recommendation approaches such as collaborative filtering (CF) methods [3], KB systems offer a functional knowledge able to reason about the relationship between a state (initial or subsequent) and a potential recommendation [18] while CF methods suffer from the so called: cold start problem [32], i.e., new users with no prior interaction history with the system from which to derive recommendations for personalised therapy plans. Lastly, the use of fuzzy sets allows experts to express their (sometimes vague) assessments/criteria by means of linguistic terms, which can be directly associated to abstract terms commonly used in therapy delivery and assessment. These advantages are corroborated through the practical scenario in which the proposed system was evaluated to have a significant occupational impact on therapists ability to provide efficient and consistent care assessment regardless of the number of sessions with particular patients.

7. Conclusions and Future Work

In this paper we have presented a game based cognitive stimulation system for analysing unobtrusively the performance of Alzheimer's sufferers during their interactions. Besides delivering cognitive therapy as other CACT systems, the novelty of the proposed system is that it is able to provide an auto adaptive computer-assisted therapy approach which can reduce input of the therapist in terms of assessment and plan formulation. This can help to decrease cognitive effort and assessment of inconsistencies arising from changes in medical staff. Such "automation" non-existent in current CACT systems, also enables learning different types of patients performance in order to assess different interactions and more effectively use the therapists' knowledge to provide consequent plan formulations according to the individuals cognitive abilities and disease pathway.

We have shown in Fig. 4 that IoT connected dialogue devices for performing cloud-enabled sentiment analysis and affect recognition can be integrated with the stimulation therapy monitoring to provide richer behaviour and cognitive condition information which can be used as part of a pervasive m-health framework tailored to the patient's individual personality characteristics and care needs.

Preliminary experiments were conducted based on patients' interactions with the Mente Activa software that found: (1) observed performance improvements on patients' interactions after a period of using the system; (2) acceptable levels of agreement from therapists towards the automatically generated stimulation plans; (3) levels of difficulty suggested by the system are responsive to patients performance; (4) the integration of an IoT connected device for emotion detection could be used to enhance the therapy scenario and provide a contextual marker against which patients performance and mental state could be better understood. These combination of findings suggests that the presented CACT system can support therapists by providing a more accurate performance and mental health analysis of patients through an automated and consistent selection of cognitive assessments which can help to significantly reduce their workload.

In the future, we aim to perform more extensive experiments integrating the IoT enabled device for sentiment analysis as well as evaluating on larger patient groups in order to analyse the effects of the system's recommendation on performance changes (due to cognitive decline).

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