Physiological-based Dynamic Difficulty Adaptation in a Theragame for Children with Cerebral Palsy

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Abstract: The purpose of this research is to provide a physiological-based Dynamic Difficulty Adaptation (DDA) for rehabilitation of children with Cerebral Palsy (CP). In this paper, we present all the steps of the DDA development by going through (1) the acquisition of physiological signals, (2) the extraction of the physiological signals' features, (3) the training of a learning classifier of physiological signals' features, and (4) the implementation of the DDA in a game-based rehabilitation system. As a result, we successfully implement a physiological-based DDA based on the user affective state (anxiety and boredom).

1 INTRODUCTION

Research and development in game-based stroke rehabilitation (theragame) spreads increasingly. The main advantages of the gaming approach are: (1) a more effective rehabilitation through an increase of the motivation (Hocine and Gouaich, 2011), (2) an access to quantified data, (3) the possibility to repeat and to adapt the exercises, and (4) the possibility to scale the rehabilitation (McCue et al., 2010).

Children are most likely to lose motivation in front of a repetitive exercise than adults (Liebert et al., 2006). Since the repetition is necessary in the rehabilitation process, it is important to keep them motivated. A way to do it is by keeping them in the flow state (Huang et al., 2010).

The flow (refer Figs. 1 and 2) is "a state in which people are so involved in their activity that nothing else seems to matter; the experience itself is so enjoyable that people will do it even at great cost, for the sheer sake of doing it" (Csikszentmihalyi, 1990).

The flow has been used in several researches to measure the enjoyment of a user in interactive applications. The idea behind the flow theory can be summarized as follows: (1) the user is more susceptible to be in the flow state when the challenge equals the skill, (2) if the challenge is less important than the skill, the user is bored (too easy for him/her), and (3) if the challenge is more important than the skill, the user is frustrated (too hard for him/her).

There are several reasons of why a simple selection of the level of difficulty (easy-medium-hard), at the beginning of the application, may not be sufficient: (1) there is a limited difficulty variation, (2) there is a difficulty gap between levels, (3) it is not enough responsive to player learning, (4) it is time-consuming to implement those variations and (5), the user has to «guess» his/her level regarding the levels of difficulty. The DDA's main advantage over non-dynamic difficulty adaptation is the possibility to automatically adapt itself from the user actual performance.

In this context, we are developing the Children Rehabilitation Project (CRP) which is based on a new modular adaptive system dedicated to rehabilitation of children having CP. The system has been designed as a framework permitting to easily implement rehabilitation applications. The first theragame developed in the context of the CRP is the Rehab-Island theragame (Fig. 3). In this application, the user controls the avatar through a Kinect™, and must touch objects by moving his/her left arm. The application parameters (such as objects' velocity, size, etc.) are decided by the therapist. In the next section, we survey the state of the art concerning Dynamic Difficulty Adaptation (DDA). In section 3, we present the proposed approach. Section 4 is dedicated to the software implementation of our system. In section 5 we

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describe the feature extraction protocol. Section 6 presents the training of the classifier. Section 7 presents the implementation of the DDA. Section 8 provides a short discussion of our method. The paper ends by a conclusion and gives some tracks for future works.

2 STATE OF THE ART

Cerebral Palsy (CP) refers to various motor impairments caused by damage to the motor control center of the developing brain, and can occurs during pregnancy, during childbirth, or after birth up to about age three (Aisen et al., 2011). Children having impaired motor movements after CP need physical therapy, which can be enhance by rehabilitation applications (Parsons et al., 2009).

There are only a few papers presenting a Dynamic Difficulty Adaptation (DDA) for stroke or CP rehabilitation systems. Moreover, in all those papers, DDA is only based on user's performance (mainly score). For example, Parnandi et al., (2013) proposed an approach based on control theory's principles. They used variation of actual and desired arousal of the user as the variation error to minimize.

Huang et al., (2010), following the work of Hao et al., (2010); and Li et al., (2010), presented Real Time Computational Intelligence (RTCI) and Adaptive ANN Computational Intelligence (ANNCI) approaches for NPC, both being based on Monte-Carlo Tree Search (MCTS).

Wong (2008) also presented an ANNCI approach, but not based on MCTS. Hocine and Gouaich (2011) described an approach based on prior assessments of the capability of the user. The adaptation is done through an ability zone, which contains information on the difficulty to do a given task at given position. They conducted an experiment on 8 subjects through a reaching-task application.

Gouaïch et al., (2012), following the work of Hocine, proposed a digital pheromone approach based on the ant algorithm introduced by Dorigo and Stützle (2004). The adaptation is done through an ability zone updated regarding user's performance. They conducted an experiment on 10 subjects through a reaching-task application.

Arulraj (2010) proposed a differential learning approach for NPC. The agent learning-rate reduces with time, while being impacted by user's performance. The approach feasibility has been tested using the Minigate game. Andrade and Ramalho (2005) and Tan et al., (2011) both proposed a Reinforcement Learning (RL) approach for NPC. G. Andrade implemented it by using the Q-learning algorithm, the adaptation being done by choosing the action-value which fit the level of the user. C. Tan implemented it by using Adaptive Uni-Chromosome Controller (AUC) and Adaptive Duo-Chromosome Controller (ADC) algorithms, the adaptation being done by activating controller's behaviour which fit the level of the user.

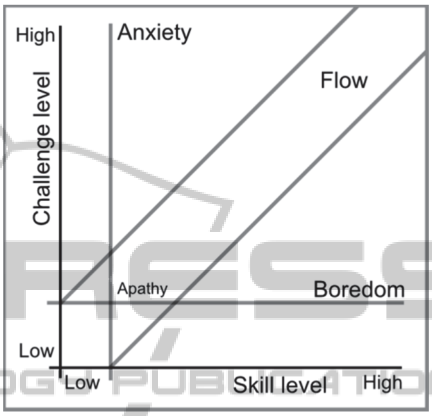

Figure 1: Out-dated version of the flow theory. Researches on affect-based DDA mainly use it, since it is easier to apply than the updated version of the flow theory.

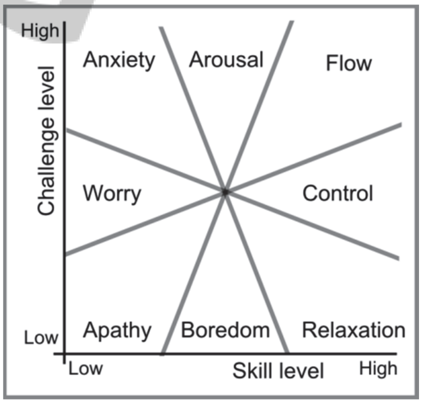

Figure 2: Updated version of the flow theory. apathy, anxiety and boredom are still used.

Regarding physiological based DDA, the DDA is usually handled through the flow theory, where the emotional states captured orient the DDA to move the challenge to emotional state.

Liu (2009), showed that a player's affective state can be deciphered from his physiological state during gaming, and that a DDA can be based on the affective state. They conducted an experiment on 9 subjects, and investigate several classification algorithms to test the affective models (Regression Tree, K Nearest Neighbours, Bayesian Network

Technique, and Support Vector Machines (SVM)). They showed that the majority of the participants improved during the affect-based DDA session, and that they perceived the game more challenging with an affect-based DDA than a performance based DDA.

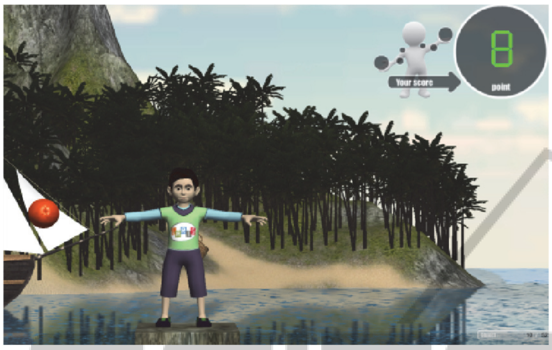

Figure 3: Illustration of the Rehab-Island application. The avatar's arms follow the user's arms through the Kinect™.

Chanel and Rebetez (2011) developed a DDA to maintain player in flow through an affective model based on EEG signals. They showed that the affective state was changing when playing Tetris. They then trained a classifier to recognize the affective state in order to adapt Tetris.

Guillaume et al., (2012) proposed a method to implement an affect-DDA in games. They recorded the player's physiological signals and then extracted the signals' features when the player was (1) playing the game and was (2) in a given affective state (such as boredom). They then trained a learning classifier to recognize the affective state from the physiological features. Finally, they used the learning classifier to know the affective state of the player (boredom or not) and use that information to adapt the game in real-time.

Parnandi and Ahmed (2014) presented Chill-Out, an adaptive biofeedback game monitoring the breathing rate of the player and adapting the game in a way that encourages relaxing behaviours. They showed that such an adaptation led to improved performances.

3 APPROACH

We decided to use a simple approach to do our DDA. Based on the user's physiological state a learning classifier identifies the user's affective state. This affective state is then passed to our DDA algorithm (refer Figs. 4 and 5) which adapts accordingly the level of difficulty of the theragame. This approach allows us to use the flow theory, which depends of the user's affective state.

The flow theory uses several affective states. The out-dated flow theory use anxiety, boredom and flow, while the updated flow theory uses apathy, worry, anxiety, boredom, arousal, relaxation, control and flow. In our work, we decided to use only anxiety and boredom, since (1) they are very relevant to the flow theory (already present in the out-dated version), (2) they have already been used in physiological-based DDA (Liu et al., 2009), (Giakoumis et al.,).

In previous works anxiety and boredom have been already classified using (1) ICG, BVP, EMG, ECG, EDA (or GSR) and heart sound features (Liu et al., 2009); (2) ECG and EDA (or GSR) features for boredom (Giakoumis et al., 2011).

Since anxiety is closely related to the stress affective state, which can be detected from ECG and EDA features, we decided to only use ECG and EDA. It allow us (1) to have less constraint in our material choice (since it is then supposed to be used with children having CP in rehabilitation, we had to limit the captors), (2) to use the same signals for both the anxiety and boredom.

In summary, from the choice of detecting anxiety and boredom, we decided to use ECG and EDA signals. We decided to use BITalino™ in order to record them. Concerning the features choice and extraction, we based our work on the previous work done by Lieu C. et al and Giakoumis D. et al. We selected 14 different features, based on ECG and EDA signals (see table 1).

Table 1: Features extracted from EDA and ECG.

Signals	Features
EDA	EDA Mean; EDA SD; EDA 1 derivation average; EDA 1 derivation RMS; EDA SCR; EDA 1 difference raw data; EDA 1 difference normalized data; EDA 2 difference normalized data.
ECG	IBI RMSSD; IBI Pnn50; IBI 1 difference raw data; IBI 1 difference normalized data.

We then used those features to train a SVM. While others learning classifier (such as Regression Tree) may give better results, we felt more confident about the SVM, which usually gives good result in emotion classification (Yoo et al., 2007).

We decided to train 2 SVM, one trained to recognized anxiety, and the other one to recognized boredom. Since, to the best of our knowledge, no method exists to recognize flow, we thought that detecting the absence of anxiety or the absence of boredom would indicate that the user was in flow.

We decided that if there was no anxiety and boredom detected, and that if the level of difficulty was above or equal to 10%, the user was in flow. If there was no anxiety and no boredom detected, and that if the level of difficulty was below 10%, the user was in apathy. If the user was in flow, then the difficulty will not change. If the user was in apathy, then the difficulty will increase (to stimulate the user). If there was anxiety and no boredom, then the difficulty will decrease. If there was no anxiety and boredom, then the difficulty will increase. If there was anxiety and boredom, then the difficulty will not change, since it may be an error in the signals reading. The figures 4 and 5 summarize the idea.

The DDA algorithm can be explained in those few lines: the application change the difficulty until anxiety/boredom is not detected and the difficulty is above a given threshold.

4 IMPLEMENTATION

We used the BITalino Board Kit™, a low cost device able to record EMG, ECG, EDA (Guerreiro and Martins, 2013) in order to record ECG and EDA. While fairly new, it is already world-wide used.We decided to use it since it was: (1) Cheap, others materials commonly used in research (such as Procomp5) are above the thousands of €; (2) Described in the literature; (3) Delivered with a SDK and (4) Wearable.

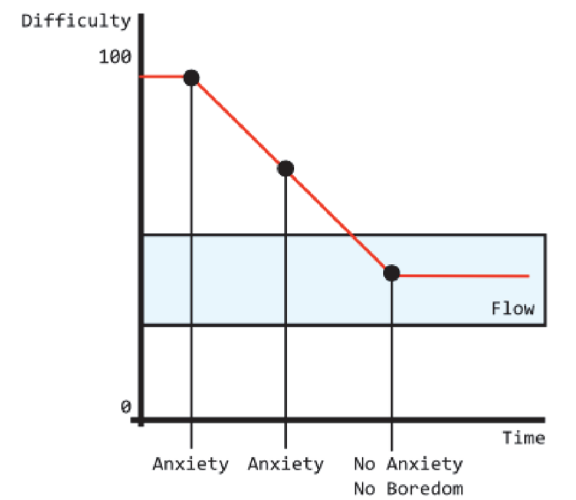

Figure 4: When anxiety is detected, the level of difficulty decreases over time, until it reaches another affective state.

We developed a BITalino C# SDK (.NET 2.0) based on the BITalino Java SDK in order to implement BITalino in Unity3D (v4.5x).

By doing so, we successfully implemented BITalino in Unity3D (see Fig. 6). It allowed us to record in real-time ECG and EDA signals.

We also developed several Unity scripts to allow us to set the BITalinoTM parameters from the application (such as the frequency). The BITalino C# SDK as well as our Unity's scripts is available online in the API section of the BITalino official website.

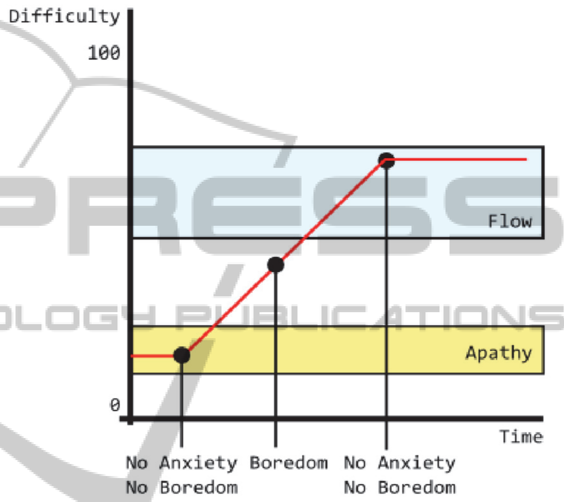

Figure 5: If the level of difficulty is to low (< 10%), we consider that the user is in the apathy state.

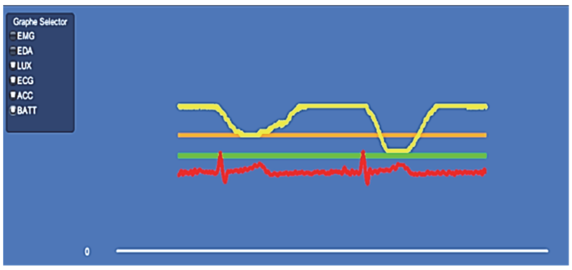

Figure 6: BITalino™ working inside Unity3D. We can see in red the ECG signal. In the left panel, we can select which signals to display.

5 FEATURES EXTRACTION

BITalino™ did not provide software to extract physiological features. Therefore we had to implement a feature extraction system ourselves. While the calculations were fairly easy to do, we decided to do it using a MATLAB C-shared DLL, to be able to use some built-in MATLAB functions. We did it in order to be able to easily change and adapt the algorithms.

It could however also have been done directly in C# through mathematical libraries. We developed several MATLAB scripts able to extract the features we were interested in (see table 1). We then exported the scripts through a C-shared DLL, to be able to call them from Unity3D.

Concerning the features extraction calculation, we followed the work previously done by Giakoumis, D. et al. The scripts were able, from the ECG and EDA raw data, to automatically extract the features of the table 1. The raw data were sampled (at 255 Hz, from the 1000 Hz raw data), then normalized and smoothed with a local regression filter.

The ECG signal was measured using three electrodes placed in lead II (negative electrode on the right arm, positive electrode on the left leg). This placement allowed the subjects' arms to move freely. The EDA signal was measured using two electrodes in bipolar placement on the left (or right) hand (index and middle finger). Even if it was as less restrictive as possible, this placement requires the subjects' left (or right) arm to not move. By doing so, we successfully managed to extract the features within Unity3D, from the signals recorded by BITalino, in real-time.

6 CLASSIFIER TRAINING

We integrated LibSVM (Chang and Lin, 2013) in Unity3D; through one of its open-source implementation available in C# (We slightly modified it to be able to use it in .NET 2.0). To train the SVM, we developed an application (ProvokeAffect) able to put the user in boredom affective state and anxiety affective state.

We developed three scenes in ProvokeAffect: (1) boredom scene, (2) anxiety scene, (3) excitement scene. Each of those scenes follows the same rules: A message displays the name of a colour (Red; Blue; Green). The subject have to click (one time) on the sphere having the named colour. After few seconds (or milliseconds) the colour's name changes. If the subject clicks on the sphere before the time limit, he gains 1 point. If he does not click on the sphere before the time limit, or if he misses, he loses 1 point. The differences between each scene depend of the: (1) overall difficulty, (2) environment (sounds, background). To provoke boredom, the interval of time between each message change is set to 4 seconds, without difference between (1) colour's spheres, (2) colour's message. Moreover, the sphere's number is 2.

To provoke anxiety, the interval of time between each message changes is set to 0.85 seconds, with a difference between (1) colour's spheres, (2) colour's message. Moreover, the sphere's number is 3. In top of that, the anxiety scene has a score-DDA to increase difficulty if the user is doing too well. The DDA (1) changes the interval of time between each message (minimum: 0.5s; maximum: 0.85s), (2) changes the shape of the sphere, (3) changes the background colour, (4) produces heart-beat sound.

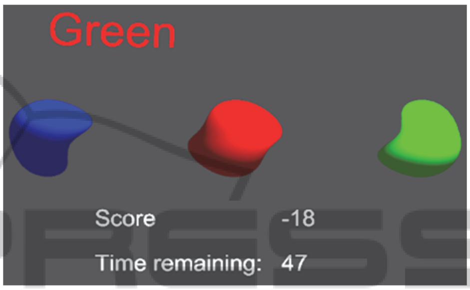

Figure 7: Anxiety scene. We can see that the message is coloured in a different way from what is intuitively supposed to be (red instead of green).

To provoke excitement, the interval of time between each message changes is set to 1.5 seconds, with a difference between (1) colour's spheres, (2) colour's message. Moreover, the sphere's number is 3. In top of that, the excitement scene has a score-DDA to increase difficulty if the user is doing too well. The DDA changes the interval of time between each message (minimum: 0.75s; maximum: 1.5s). Finally, it is possible to do several series of combo. Successful combo produces (1) score increase, (2) sounds effects. Note that we did not use the excitement scene to train a SVM dedicated to excitement (the preliminary results did not show a great difference between anxiety and excitement, so we preferred to not use it), unlike the anxiety and boredom scene.

Having the ProvokeAffect application, we did a preliminary test to see if there were noticeable differences between anxiety and boredom scene when looking at the physiological signals.

We can see that, even without looking at the features, there are important differences between "EDA boredom" and "EDA anxiety" signals (see Figs 8 and 9). Concerning the experimentation relative to the training of the learning classifier, we used all three scenes of ProvokeAffect. All the experimentation (including the Likert-scale test) was automatized, in order to not induce change(s) in the affective state of the user. The experiment was 15 minutes long. After an explanation of the rules (automated), the user had to pass 3 trials of the boredom scene, then 3 trials of the anxiety scene, then 3 trials of the excitement scene. The change between the scenes was automated. Between each trials, there was a one minute during which the subject had to fill a 5 Likert-scale self-report (still automated).

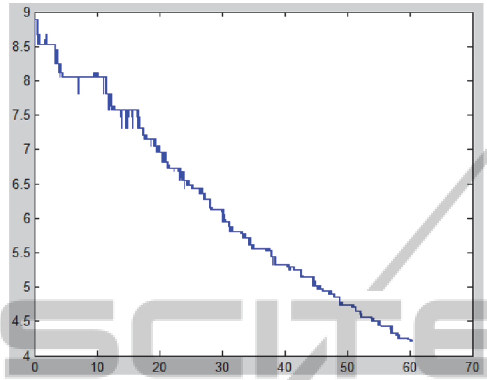

Figure 8: EDA when doing the Boredom scene of ProvokeAffect.

The Likert-scale comported several non-relevant questions to our experiment in order to not orient the subject in his answers. As relevant questions, we asked if he was bored (1-5) or if he was anxious (1-5). After the experiment, we labelled the results as anxiety / boredom if the user answered 4 or 5 and not anxiety / boredom if it was 1 or 2. If it was 3, then we did not include the result. Finally, we had 10 subjects who did the experiment (and therefore a total 90 trials). From those labelled features, we trained the two learning classifier (one for anxiety recognition and one for boredom recognition).

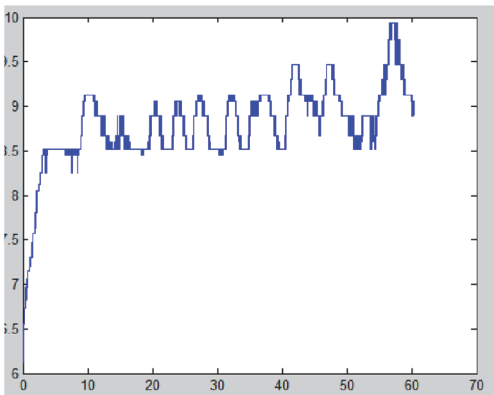

Figure 9: EDA when doing the Anxiety scene. We can clearly see that there are a lot more of SCR than with the Boredom scene of ProvokeAffect.

By training our SVMs (after grid-search) we obtained a cross-validation result up to 75% for both anxiety and boredom SVM. While this result is below other studies (probably because there was not enough trials), it was enough to continue our work on our affect-DDA.

7 IMPLEMENTATION OF THE DDA

Since the DDA is supposed to be used by different theragames, it was important to decouple it from the theragames into a DDA module. The DDA module comports the reading of physiological signals, the features extraction, the SVM classifiers and the implementation of the DDA algorithm. The DDA module gives to the theragames a difficulty level between 0-100, which may change over time (unless the user is in flow). 0% correspond to the easiest difficulty while 100% correspond to the hardest difficulty.

It is then up to the developer of each theragame, according to a value of difficulty in percentage (which may change over time) to implement the "meaning" of such difficulty. For example, in our Rehab-Island theragame, we observed that the difficulty was mainly dependant of 4 main different variables. We gave to each of those variables a minimum and maximum value, which follow a linear, exponential or logarithmic curve. By doing so, when the difficulty is updated, each of our difficulty variables is automatically updated. However, this is a pretty straightforward example. There are others ways to implement the difficulty, which depend mainly of the kind of game developed.

8 DISCUSSION

By decoupling our DDA from our theragame, we successfully managed to implement it in the CRP. In summary, we implemented a physiological-based DDA, which, through the affective-state (boredom and anxiety states) of the user, adapts the difficulty. At the best of our knowledge, there is non-yet a physiological-based DDA using boredom and anxiety state together. There is non-yet either a physiological-based DDA in a theragame.

Even if our work present a working solution to a physiological-based DDA implementation in an adaptive interface, its purpose was to be the base of researches in rehabilitation using DDA. We would like to see if a physiological-based DDA is more effective than score-based DDA in CP's rehabilitation, and in what ways it is more effective. We would also like to try others devices than

BITalino (such as the Kinect 2, able to track the blood flow of the user). Eventually, we would also like to improve the existing system, by training a more accurate classifier (Liu et al., suggested to use a Regression Tree classifier).

9 CONCLUSION AND FUTURE WORK

We successfully managed to implement a philological-based DDA in an adaptive interface (the CRP). This DDA uses the EDA and ECG signals of the user. From those signals, it extract its important features (such as GSR and HR), in order to accurately classify user's affective state. Using 2 trained SVM (one for boredom affect state, one for anxiety affect state), the DDA is able to know if the user is bored, anxious or likely to be in the flow affect state, and therefore to increase, decrease, or not change the difficulty. By providing such a DDA, we would like to propose a more effective DDA in order (1) to improve rehabilitation, (2), to allow the patient to be less dependent of the patrician.

In our future study, we will see if the physiological-based DDA presented in this work is more effective than a straightforward score-based DDA in CP's rehabilitation. To do so, it will be necessary to retrain the SVMs, since the SVMs data in our experiment came from adults, and CP rehabilitation is for children. During the training, it will be also necessary to propose a "boring" application and an "anxious" application which ask the user to perform a physical effort on his upper-body. Luckily enough, Rehab-Island seem adapted to propose such applications.

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