# Detecting affective states in virtual rehabilitation

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***Abstract*— Virtual rehabilitation supports motor training following stroke by means of tailored virtual environments. To optimize therapy outcome, virtual rehabilitation systems automatically adapt to the different patients' changing needs. Adaptation decisions should ideally be guided by both the observable performance and the hidden mind state of the user. We hypothesize that some affective aspects can be inferred from observable metrics. Here we present preliminary results of a classification exercise to decide on 4 states; tiredness, tension, pain and satisfaction. Descriptors of 3D hand movement and finger pressure were collected from 2 post-stroke participants while they practice on a virtual rehabilitation platform. Linear Support Vector Machine models were learnt to unfold a predictive relation between observation and the affective states considered. Initial results are promising (ROC Area under the curve (mean±std): 0.713 ± 0.137). Confirmation of these opens the door to incorporate surrogates of mind state into the algorithm deciding on therapy adaptation.**

***Keywords*—affective computing; virtual rehabilitation; stroke; hand; motor recovery***

## I. Introduction

Emotions influence human health and the willingness to perform daily activities. Affective computing (AC) is a relatively new field whose main focus is to identify and simulate emotions while people interact with computers. A lot of efforts in affective computing are dedicated to identify the user's emotions through the interaction with the computer. The user's emotional state is not directly observable, but his/her emotions are expressed through three channels: 1) audio (speech), 2) face and body gestures/movements (visual) and 3) internal physiological changes (heart beat rate, respiration, blood pressure, skin conductance, body temperature, etc.) [1]. Detection of user's affective states, permits the implementation of empathic interaction strategies.

In 2009, stroke was the principal single cause of adult disability in the developed world [2]. A common sequela to survivors is motor disability of the upper limb. Rehabilitation therapies help to patient to recover his/her mobility; but the current administration of these therapies is still far from optimal [3, 4]. Virtual rehabilitation (VR) is a relatively novel alternative for the delivery of physical or occupational therapies. VR platforms hide the rehabilitatory exercises behind the movements required for controlling an avatar within ad-hoc computer generated environments. In the process they favour some of the basic principles of rehabilitation: repetition, feedback, motivation and task specific training [5]. Particularly, patient motivation is crucial to exercise adherence [6] and emotions are involved in this [7]. It follows that mining the affective state of the user can be exploited to design motivating VR sessions.

Unobtrusively measuring a hidden variable is never easy often requiring the definition of observable surrogates. When not consciously inhibited, our behavioural gestures may convey information about our affective state. For instance, it may be conjectured that gripping force may be affected by tension. Our hypothesis is that 4 affective states; tiredness, tension, pain and satisfaction, are recuperable from basic motor measurements of hand kinematics and pressure exerted upon gripping.

Previously, we have developed Gesture Therapy (GT) a virtual rehabilitation platform which has been previously described [5]. GT incorporates a physical controller or gripper, that the patient holds with the affected hand to reach some goals in the games. If our hypothesis is correct, we should be able to recover some of the aforementioned affective states capitalizing only on the 3D trace of hand locations and the pressure sensed by the gripper. Inference of affective state may later be exploited to design empathic interfaces adapting to the user emotional conditions.

A small feasibility pilot is presented here whereby 2 stroke patients are exposed to Gesture Therapy while the session is video recorded and data from the controller is saved for subsequent analysis. Data was tagged by a human with domain knowledge and a rather naïve classification strategy was implemented. Our aims at this stage are humble; establishing whether recovery of the affective states is viable from the controller’s output. Without implying causal relations –i.e. explanatory power, nor aiming to control any aspect of the game flux yet –i.e. online demands, it suffices for our purposes at this point to offline achieve a high predictive power. How high is high in this context depends on the posterior usage, and thus we don’t aim for any predefined threshold, although we hope to be well above random choice. The classification strategy can later be optimized by model selection tools [8] if needed. Moreover we are happy to accept variable success across the 4 studied states.

## II. RELATED WORK

### A. *Affective Computing*

Affective Computing is a subfield of Human-Computer Interaction (HCI), exploring whether computers may have the ability to recognize human emotions, ideally at the same level that a person can do [9]. Research in affective computing has dedicated strong efforts to decode some user affective states through facial expressions, generally using the FACS (Facial Action Coding System) code [10-12], linguistic expressions [12, 13] and non-linguistic, such as laughter, sigh, cough, among others [10], tracking and monitoring human body while walking, talking, etc. [14-17]. Many experiments focus on recognizing a set of six universal basic emotions: happiness, sadness, surprise, fear, anger and repugnance [10]. Beyond these, Picard [18] asseverates that measuring the frustration level caused by a technology can allow to pinning down its cause and work to prevent or reduce it. Other efforts have been made to detect boredom, fatigue and pain from the face in recorded videos when the person has spontaneous facial expressions [19, 20].

There are still many open challenges in affective computing, since there are a variety of emotions and difficulties to distinguish each other. Moreover, in many cases it is necessary to take into account the context in which the affective state is measured [10]. However, although the problem is difficult, obtaining a partial solution is still valuable and useful. It can contribute to an intelligent interaction that benefits the health and productivity of human beings [9].

### B. *Affective Computing in Rehabilitation*

Coming closer to the domain at hand, Aung et al. [20] studied the level of chronic pain in the lower back. In this work, experts labelled the presence of pain by observing the face of 21 patients. Then using Support Vector Machine (SVM) as the classification method, they report a ROC (Receiver Operating Characteristics) Area Under the Curve (AUC) of 0.658. Partially observable Markov decision process (POMDP) have been used in rehabilitation of the upper extremity in stroke patients to modify exercise parameters so that the system adapts to the patient specific needs; the patient fatigue was included in the model [21]. In Bonarini et al. [22], the authors studied 5 levels of stress in rehabilitation protocols, from biological signals, such as blood pressure, skin conductance, electrocardiogram (EKG), respiratory rate, electrical activity of muscles (electromyogram: EMG) and temperature; with the classification algorithm k-NN (k-Nearest Neighbor) with k = 11, testing with 6 healthy people and achieving a precision (accuracy) of 88%.

Meanwhile, for Gesture Therapy, S. Avila et al. [23] built a module based on a Markov decision process (MDP) and reinforcement learning (RL) to adapt the therapy using 2 variables: the patient speed to achieve the games targets and the control of his/her upper limb while moving to those targets. The adaptation consists in optimizing game challenge (adjust game difficulty) according to patient’s performance [5]. The authors suggested as part of future work, taking into account the patient's frustration or fatigue to improve the adaptation module [23]. A difference of this work with previous research is that we are using only motion and pressure from the affected limb to infer the affective state, as we want to avoid additional sensors not already available in Gesture Therapy.

## III. METHODS

The objective is to determine the affective state of the patient, in particular those states that seem relevant for rehabilitation, based on the user’s interaction with the rehabilitation platform. Thus, we consider as independent variables the 3D coordinates of the movements of the gripper the patient controls with the affected limb and his/her hand pressure on it; and as dependent variable the affective state. The possible affective states were selected in agreement with a group of experts in psychology and affective computing. This selection is explained in the following sub-sections.

### A. *Gesture Therapy*

Some changes were made in a module of Gesture Therapy to save the 3D coordinates and the pressure exerted upon the gripper. In Fig. 1 we can see a demonstration of the platform.

Fig. 1. The Gesture Therapy platform. One of the researchers is illustrating the use of it. The gripper, hold with the left hand here, serves to control an avatar on the virtual scenario. 3D location of the hand and gripping pressure are sensed and send to the computer for further processing.

### B. *Patient recruitment and data collection*

Potential participants were identified by health staff from the National Institute of Neurology and Neurosurgery of Mexico (in Spanish: Instituto Nacional de Neurología y Neurocirugía or INNN), Mexico. Following a brief summary on the experiment goal, 2 patients accepting to participate signed an agreement form including acknowledging to video recording of the session for scientific purposes.

The number of rehabilitation sessions was 10, each one lasting 45 mins on average, although playing time was lower – the rest of the time including stretching exercise, game switching, etc. Gesture Therapy was the VR platform used. Sessions were supervised by a qualified expert occupational therapist with previous experience on Gesture Therapy. Each session took place in a different day. Data collection was organized to take place in each virtual rehabilitation session for each patient. Gesture Therapy registered the following data:

- 3D coordinates of gripper ball, proxy of the hand location at 30 Hz, by video tracking as regularly for GT.
- Gripping pressure exerted on the gripper by the affected upper limb. The gripper incorporates a pressure sensor on the front.
- Frontal digital video of the patient while doing the therapy and showing the face expressions and the hand movements, see Fig. 2.

The patients further answered the intrinsic motivation scale (IMS) questionnaire at the end of each session.

Fig. 2. Patient participation in the Gesture Therapy platform.

### C. *Affective states selection*

Choice of affective states was made with the participation of experts in the field of rehabilitation and in the area of psychology and affective computing. The experts recommended the affective states of tiredness, tension, pain and satisfaction, after the consideration of what is important in stroke patient rehabilitation and the IMS.

The affective states of tiredness, tension and pain correspond to undesired situations, which if detected automatically, could help Gesture Therapy's adaptation module to suggest a decrement in game challenge, or perhaps suggest a break. The remaining affective state, satisfaction, is a desired state and may as well provide guidelines to game challenge adjustment or identifying patient's preferences.

The patient's observable performance is the factor to adjust game difficulty in Gesture Therapy at present. The incorporation of the affective states variables must be done based on the advice of medical experts. The adjustment of the game's difficulty levels will be done combining performance indicators and the affective state of the patient.

### D. *Labelling*

The video frames were synchronized with the record of the movements and the pressure. The movements, pressure and frames were labelled by visually inspection of the videos from each session and taking into account the IMS. Short video clips from the full video sequence corresponding to gaming periods were extracted for labelling by one of the researchers. Each video clip lasts about 1 minute. The raters labelled the intervals of frames where they consider the patient show some of the selected affective states: tiredness, tension, pain or satisfaction using software ELAN - Linguistic Annotator 4.7.0 [24], see Fig. 3. Since the frames have a direct correspondence with the 3D hand location and the pressure (synced), this is equivalent to having a direct labelling of all three data streams; video itself, but also hand location and pressure. The video information (patient's expressions and other body movements) was used only for the labelling, but importantly not included in the classification model. Raters were blind to each other.

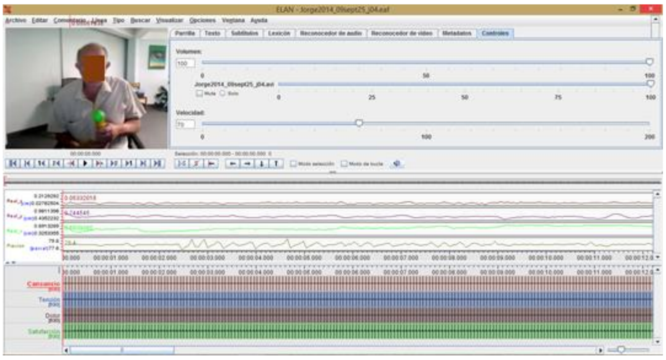

Fig. 3. Using ELAN - Linguistic Annotator 4.7.0 to label the interval of frames where the rater consider the patient show some of the selected affective states: tiredness, tension, pain or satisfaction.

### E. *Feature extraction*

We assume that emotions may be associated with certain motion and pressure patterns, i.e., hand gestures and pressure, rather than a specific value of these variables. Eight features were extracted from the data collected to characterize the dynamic behaviour of the movements and pressure on the gripper.

Gesture Therapy records the stream video at 30Hz, so the video has 15 frames per second. Given $Tfr = 1/15$ secs (time of a frame in GT video), 2 points: $p_i = (x_i, y_i, z_i)$ and $p_{i+1} = (x_{i+1}, y_{i+1}, z_{i+1})$, where $p_i, p_{i+1} \in [0,1]^3$. Given $P_i$, the pressure in the frame $i$, $P_i \in [0,1]$ ($p_i, p_{i+1}, P_i$ are normalized), the eight features are:

- *Sm*: speed of movement in space (meters/second), see Eq. (1),

$$Sm_{i+1} = \sqrt{(x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2 + (z_{i+1} - z_i)^2} \; / \; Tfr \quad (1)$$

- *Am*: acceleration of movement in space (meters/second$^2$), see Eq. (2),

$$Am_{i+1} = |Sm_{i+1} - Sm_i| \;/\; Tfr \quad (2)$$

- *Dx*: differential location (distance) along the x axis (meters), see Eq. (3),

$$Dx_{i+1} = |x_{i+1} - x_i| \quad (3)$$

- *Dy*: differential location (distance) distance along the y axis (meters), see Eq. (4),

$$Dy_{i+1} = |y_{i+1} - y_i| \quad (4)$$

- *Dz*: differential location (distance) distance along the z axis (meters), see Eq. (5),

$$Dz_{i+1} = |z_{i+1} - z_i| \quad (5)$$

- *AvP*: average pressure (kiloPascals),

- *Ps*: pressure speed (kiloPascals/second), see Eq. (6),

$$Ps_{i+1} = |P_{i+1} - P_i| \;/\; Tfr \quad (6)$$

- *Pa*: pressure acceleration (kiloPascals/second$^2$), see Eq. (7).

$$Pa_{i+1} = |Ps_{i+1} - Ps_i| \;/\; Tfr \quad (7)$$

Since the hand movement (varying location) and pressure represent a trace in time, they can be handled as a time series. In this sense, it is possible to shift a window of length *W* [samples] in the series and calculate the local value of the 8 attributes described to reconstruct their timecourse. Suppose a window sized *W = 3*, then we take 3 consecutive sample points in the series: $p_{i-1}$, $p_i$ and $p_{i+1}$, and we calculate:

- average speed: $Sm_1$ and $Sm_2$, where $Sm_1$ is the speed between $p_{i-1}$ and $p_i$, and $Sm_2$ is the speed between $p_i$ and $p_{i+1}$,
- average acceleration, in this example we have only two speeds $Sm_1$ and $Sm_2$, so one acceleration value $Am_1$ (speed change per unit time) is obtained,
- average distances (marginal differential locations) for each axis; $Dx_1$, $Dy_1$ and $Dz_1$ between $p_{i-1}$ and $p_i$, and $Dx_2$, $Dy_2$ and $Dz_2$ between $p_i$ and $p_{i+1}$,
- average of the pressures observed in the window, for this example there are three pressures, so $AvP = (P_{i-1} + P_i + P_{i+1})/3$.
- average speed of the pressure changes; in this case we have two pressure changes $Ps_1$ from $P_{i-1}$ to $P_i$, and $Ps_2$ from $P_i$ to $P_{i+1}$,
- average of the pressure accelerations $Pa_1$; in this example, there is a single value because there are two speeds of pressure changes.

Bigger windows may result in further values. In other words, at each sample in the time series, from a neighbourhood of that sample, a new pattern (or example to the classification process) is obtained. Since at least 3 points are needed to calculate acceleration, the minimum window size *W* should be 3.

Classes were coded separately; each sample (leading to a pattern) is assigned 4 binary labels: 1 or –1, corresponding to the presence or absence of every affective state of interest. These class labels for each affective state are obtained by majority voting (consensus among raters calculated offline), at sample $p_i$.

### *F. Classification model*

Linear support vector machines (SVM, Kernel: K(x,y) = <x,y>, c = 1.0, epsilon = 1.0 E-12) were trained to predict each affective state independently. That is, each one is a binary classifier, based on the features previously described. Since adaptation is often patient-based, we decided to train the classifiers independently for each patient.

Feature timecourses were processed with windows sized W = 5, 6, 7 obtaining the corresponding patterns. A different SVM model for each patient (2 patients), each affective state (4: tiredness, tension, pain and satisfaction), and each window value (values; 5,6 and 7) was developed for a total of 24 SVM models. Another experiment was performed by combining data from the two patients. In this case, 12 SVM models (4 affective states x 3 windows sizes) were learnt. Internal validity of the classifier model was established using 10-fold cross validation replication mechanism in Weka 3.6.11 [25].

## IV. RESULTS

Two patients: P1 and P2, were considered in this feasibility study. The demographic information about the patients is summarized in table I. Patient P1 attended to 6 sessions and P2 attended all 10 sessions. The version of Gesture Therapy installed at INNN has 5 games. Patients played the 5 games in each session except for one session of P1 in which only 4 games were played in that session, so the number of videos for 6 sessions was 29.

TABLE I. COHORT DEMOGRAPHICS AND SESSIONS

| | ***P1*** | ***P2*** |
|---|---|---|
| Age | 55 years | 57 years |
| Gender | M | F |
| Stroke date | April, 2014 | May, 2014 |
| Therapy onset | May 8$^{th}$, 2014 | Sep 24$^{th}$, 2014 |
| Paretic side | Right | Right |
| Number of sessions | 6 | 10 |
| Number of video clips | 29 | 50 |

Tables II and III report the results for P1 and P2 respectively for the 4 affective states and the 3 window sizes. Results are summarized as mean and standard deviation (std) across the 10 fold. During the labelling process patient P2 did not show affective state of pain, so there are none results for this emotion to P2. Table IV shows the results of combining the two patients data.

TABLE II. RESULTS (MEAN ± STD) FOR PATIENT P1 ACROSS THE 10 FOLD (THE GREATEST VALUE OF EACH COLUMN IS IN BOLD TYPE).

| ***Window size*** | ***Accuracy*** | ***Sensitivity*** | ***Specificity*** | ***Precision*** | ***F-Measure*** | ***ROC Area*** |
|---|---|---|---|---|---|---|
| tiredness | | | | | | |
| W = 5 | 0.798 ± 0.130 | 0.731 ± 0.229 | 0.854 ± 0.136 | 0.823 ± 0.157 | 0.758 ± 0.170 | 0.792 ± 0.137 |
| W = 6 | 0.816 ± 0.083 | 0.774 ± 0.115 | 0.852 ± 0.124 | 0.839 ± 0.121 | 0.798 ± 0.094 | 0.813 ± 0.084 |
| W = 7 | 0.827 ± 0.108 | 0.752 ± 0.190 | **0.889** ± 0.107 | **0.868** ± 0.135 | 0.795 ± 0.142 | 0.821 ± 0.114 |
| tension | | | | | | |
| W = 5 | 0.648 ± 0.087 | 0.766 ± 0.140 | 0.527 ± 0.140 | 0.628 ± 0.082 | 0.685 ± 0.088 | 0.646 ± 0.087 |
| W = 6 | 0.683 ± 0.077 | 0.812 ± 0.087 | 0.55 ± 0.143 | 0.656 ± 0.080 | 0.723 ± 0.066 | 0.681 ± 0.077 |
| W = 7 | 0.681 ± 0.059 | 0.804 ± 0.112 | 0.553 ± 0.100 | 0.651 ± 0.051 | 0.716 ± 0.061 | 0.679 ± 0.058 |
| pain | | | | | | |
| W = 5 | 0.739 ± 0.113 | 0.715 ± 0.143 | 0.76 ± 0.255 | 0.814 ± 0.174 | 0.741 ± 0.092 | 0.738 ± 0.118 |
| W = 6 | 0.780 ± 0.149 | 0.75 ± 0.333 | 0.817 ± 0.175 | 0.782 ± 0.174 | 0.722 ± 0.284 | 0.783 ± 0.162 |
| W = 7 | 0.831 ± 0.122 | 0.84 ± 0.227 | 0.835 ± 0.165 | 0.865 ± 0.124 | 0.827 ± 0.139 | 0.838 ± 0.116 |
| Satisfaction | | | | | | |
| W = 5 | 0.863 ± 0.021 | 0.850 ± 0.012 | 0.871 ± 0.031 | 0.826 ± 0.036 | 0.837 ± 0.021 | 0.861 ± 0.019 |
| W = 6 | 0.888 ± 0.017 | 0.911 ± 0.028 | 0.871 ± 0.023 | 0.836 ± 0.024 | 0.871 ± 0.020 | 0.891 ± 0.018 |
| W = 7 | **0.896** ± 0.014 | **0.934** ± 0.028 | 0.869 ± 0.020 | 0.835 ± 0.020 | **0.881** ± 0.017 | **0.901** ± 0.015 |

TABLE III. RESULTS (MEAN ± STD) FOR PATIENT P2 ACROSS THE 10 FOLD (THE GREATEST VALUE OF EACH COLUMN IS IN BOLD TYPE).

| ***Window size*** | ***Accuracy*** | ***Sensitivity*** | ***Specificity*** | ***Precision*** | ***F-Measure*** | ***ROC Area*** |
|---|---|---|---|---|---|---|
| tiredness | | | | | | |
| W = 5 | 0.718 ± 0.083 | 0.593 ± 0.165 | **0.822** ± 0.112 | **0.756** ± 0.159 | 0.649 ± 0.123 | 0.708 ± 0.083 |
| W = 6 | **0.753** ± 0.133 | **0.790** ± 0.123 | 0.723 ± 0.192 | 0.727 ± 0.163 | **0.750** ± 0.125 | **0.757** ± 0.129 |
| W = 7 | 0.736 ± 0.168 | 0.743 ± 0.148 | 0.731 ± 0.258 | 0.741 ± 0.180 | 0.729 ± 0.135 | 0.737 ± 0.163 |
| Tension | | | | | | |
| W = 5 | 0.628 ± 0.075 | 0.703 ± 0.126 | 0.553 ± 0.084 | 0.609 ± 0.061 | 0.650 ± 0.085 | 0.628 ± 0.075 |
| W = 6 | 0.602 ± 0.069 | 0.677 ± 0.113 | 0.529 ± 0.080 | 0.586 ± 0.060 | 0.626 ± 0.076 | 0.603 ± 0.069 |
| W = 7 | 0.596 ± 0.053 | 0.746 ± 0.034 | 0.448 ± 0.109 | 0.576 ± 0.052 | 0.648 ± 0.035 | 0.597 ± 0.053 |
| Pain | | | | | | |
| W=5,6,7 | - | - | - | - | - | - |
| Satisfaction | | | | | | |
| W = 5 | 0.558 ± 0.019 | 0.584 ± 0.056 | 0.533 ± 0.029 | 0.551 ± 0.016 | 0.566 ± 0.033 | 0.558 ± 0.019 |
| W = 6 | 0.566 ± 0.026 | 0.687 ± 0.034 | 0.447 ± 0.045 | 0.549 ± 0.021 | 0.610 ± 0.023 | 0.567 ± 0.026 |
| W = 7 | 0.573 ± 0.017 | 0.717 ± 0.042 | 0.432 ± 0.050 | 0.554 ± 0.015 | 0.624 ± 0.018 | 0.574 ± 0.017 |

TABLE IV. RESULTS (MEAN ± STD) FOR COMBINING THE TWO PATIENTS DATA ACROSS THE 10 FOLD (THE GREATEST VALUE OF EACH COLUMN IS IN BOLD TYPE).

| ***Window size*** | ***Accuracy*** | ***Sensitivity*** | ***Specificity*** | ***Precision*** | ***F-Measure*** | ***ROC Area*** |
|---|---|---|---|---|---|---|
| tiredness | | | | | | |
| W = 5 | 0.760 ± 0.107 | 0.647 ± 0.145 | 0.856 ± 0.106 | 0.798 ± 0.153 | 0.710 ± 0.132 | 0.751 ± 0.108 |
| W = 6 | 0.785 ± 0.082 | 0.660 ± 0.186 | 0.888 ± 0.108 | 0.857 ± 0.130 | 0.725 ± 0.124 | 0.774 ± 0.088 |
| W = 7 | **0.801** ± 0.071 | 0.664 ± 0.147 | **0.918** ± 0.077 | **0.887** ± 0.108 | **0.746** ± 0.111 | **0.791** ± 0.074 |
| tension | | | | | | |
| W = 5 | 0.622 ± 0.059 | 0.710 ± 0.078 | 0.537 ± 0.076 | 0.597 ± 0.053 | 0.648 ± 0.057 | 0.624 ± 0.059 |
| W = 6 | 0.596 ± 0.075 | 0.726 ± 0.100 | 0.474 ± 0.092 | 0.564 ± 0.059 | 0.634 ± 0.071 | 0.600 ± 0.076 |
| W = 7 | 0.657 ± 0.072 | **0.738** ± 0.067 | 0.578 ± 0.106 | 0.631 ± 0.075 | 0.679 ± 0.063 | 0.658 ± 0.072 |
| pain | | | | | | |
| W=5,6,7 | - | - | - | - | - | - |
| Satisfaction | | | | | | |
| W = 5 | 0.586 ± 0.015 | 0.482 ± 0.024 | 0.690 ± 0.028 | 0.609 ± 0.021 | 0.538 ± 0.018 | 0.586 ± 0.015 |
| W = 6 | 0.578 ± 0.017 | 0.476 ± 0.025 | 0.680 ± 0.025 | 0.599 ± 0.023 | 0.530 ± 0.022 | 0.578 ± 0.017 |
| W = 7 | 0.579 ± 0.018 | 0.473 ± 0.021 | 0.686 ± 0.029 | 0.603 ± 0.025 | 0.530 ± 0.019 | 0.580 ± 0.018 |

## V. DISCUSSION

Models for satisfaction built for Patient P1 with window W= 7, have presented ROC AUC mean of 0.901 (the highest ROC AUC in this work). Meanwhile, patient P2 obtained best result (mean 0,757) with models for automatic classification of tiredness with window size W = 6. In the labelling process P2 did not present the pain state. In table IV the prediction performance was worse than the results obtained of patient P1 (table II) and similar results of patient P2 (table III); the best result in table IV was for tiredness with window W = 7 (ROC AUC of 0.79).

Patient P1 has more situations of satisfaction and no satisfaction that are differentiable from the videos than patient P2. This might explain the higher classification for patient P1. Since P2 obtained his/her best results for tiredness and P1 had his/her second best results there, the combined data exhibited its best values with tiredness.

Some medical experts that participated in this study expressed that the most difficult affective states to label in these patients were tension and pain. In rehabilitation, pain is a particularly critical state; painful exercises may be harmful to patients' recovery. The patients involved in this study reported low levels of pain using the intrinsic motivation scale (IMS) questionnaire at the end of each session.

## VI. CONCLUSIONS

We have obtained an initial approximation to predictive models for decoding specific affective states from hand location and gripping measurements in 2 stroke patients while they interact with a virtual rehabilitation system. These results suggest that at least satisfaction and tiredness are susceptible of classification from observable data streams even if limited to naïve classification strategies. Pain and tension recovery were also above the random decision levels, but may require more aggressive models before satisfactory detection levels can be claimed. The results are promising from the point of view of using unsophisticated data analytics. A bigger trial should confirm whether this apparent trend can be generalized to the population.

Parameter *W* has no associated physiological meaning, and its value although maybe affecting specific classification rates is irrelevant for the discussion. Nevertheless, shall a more aggressive classification need of a window size, perhaps multiresolution approach can make this parameter redundant.

As part of future work, we consider to use Naïve Bayes with structural improvement [26] to understand the contribution of the different attributes in the predictive relation. Transfer learning strategies may be exploited to migrate population-based models to specific patient-based models.

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