2014 5th IEEE RAS & EMBS International Conference on
Biomedical Robotics and Biomechatronics (BioRob)
August 12-15, 2014. São Paulo, Brazil

Classifying Emotions in Rehabilitation Robotics Based on Facial Skin Temperature

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Abstract— **Rehabilitation robotic plays an important role in therapeutic exercises by combining robots with computer serious games into an attractive therapeutic platform. However, measuring the degree of engagement of the user is not a trivial task. The difficulty of applying question-based techniques, particularly for patients who have the speech capacity compromised due to cerebrovascular accidents, has inspired us to investigate noninvasive and nonverbal techniques aiming to classifying emotions. For this purpose, a supervised artificial neural network interprets facial infrared thermal images of individuals performing rehabilitation robotic therapy integrated with games. A database containing images of 8 users was generated by combining evoked and spontaneous emotional reactions. In total, 2445 facial thermal images with an average of 100 images per person for three categories of emotions (neutral, motivated, overstressed) were classified. Based on confusion matrix analysis, the experimental results correlated very well with manual estimates, producing an overall performance of 92.6%.**

I. Introduction

Rehabilitation robotic has established a new paradigm for higher efficiency and physical performance compared to the frequently tedious conventional rehabilitation process based on the repetition principle stated in [1]. The integration of a robot with computer serious games into a rehabilitation scenario has outlined a promising approach by offering sessions in a more stimulating physical re-education environment. Furthermore, rehabilitation robotic provides a repository for data analysis, diagnosis, therapy customization and maintenance of patient records.

The involvement of the user is probably one of the most important mechanisms through which therapy produces clinical benefits [2]. At the same time the engagement of the user with therapeutic exercises is an important topic in the rehabilitation robotics research field [3], the measurement of the actual motivation is not a trivial task. Relevant aspects include, but are not limited to player modeling [4], Dynamic Difficulty Adjustment [5], Physiological Signals, Motion/ Pose tracking [6] and facial expressions [7], [8].

Several studies have demonstrated that facial thermal information is related to facial expression [9], [10]. Khan et al. proposed a classification of pretended and evoked facial expressions of positive and negative affective states demonstrating that infrared imaging is useful to observe affective state specific facial thermal variations [10], [11]. Multivariate tests and linear discriminate analysis were investigated on thermal intensity values for classification of intentional facial expressions [12]. The problem of facial occlusion caused by eyeglasses on thermal images was addressed, e.g. by fusing thermal infrared and visible imagery [13]. Hernández et al. employed a Support Vector Machine committee for recognition of facial expression using Gray Level Co-occurrence Matrix-based descriptors in thermal imagery [14]. Thermal image analysis has also been used to evaluate stress-sensation [15]. The authors found a correlation between stress and the increasing blood flow in the frontal vessel of the forehead which could be monitored through thermal imaging. Pavlidis et al. proposed a concept for anxiety detection useful in critical military facilities for detecting suspects committed in illegal activities [16]. In [17] a thermal image analysis was developed as a promising method of increasing the success rate of polygraph testing, i.e. a standard security procedure. For facial expression recognition, wavelet transformation [18] and temperature difference by voting [19] have also been used.

In the context of assessing the engagement of patients undergoing rehabilitation, most techniques are based on questionnaires [20], [21] and interviews [22]. A critical review of the concept of patient motivation on physical rehabilitation can be found in [23].

Despite the large amount of works on rehabilitation robotic [24-26], only a few approaches have addressed the problem of automatically estimate patient motivation [27] in this research field.

This work employs infrared thermal images to estimate subject emotion when performing rehabilitation robotic therapy integrated with games. The facial skin temperature-based approach was chosen because of its inherently noninvasive [9] and nonverbal characteristics. Additionally, the technique may be more appropriate to deal with pour facial expression of post-stroke patients. Subsequent to the image acquisition, a supervised artificial neural network (ANN) analyzes some statistical measurement computed in different regions of the face to classify the input images into three different emotions: Neutral, Motivated and Overstressed.

The paper is outlined as follows. Section II describes the methodology used. Section III presents and discusses the results obtained. Conclusion and future work are addressed in Section IV.

II. Methodology

The framework of the approach is shown in Fig. 1.

A. *Rehabilitation Robotic System*

Experiments were conducted by recording thermal images of healthy volunteer faces during the robot-assisted rehabilitation session. The current prototype of our system was designed for rehabilitation of wrist function for cerebral vascular accident (stroke) patients (Fig. 2).

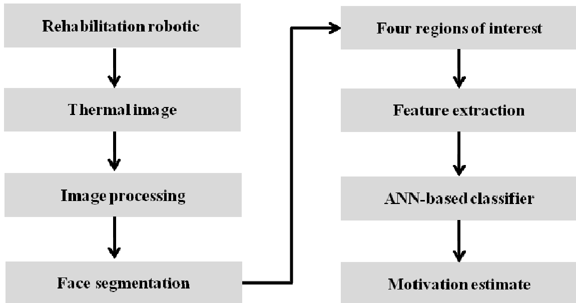

Figure 1. Block diagram of the proposed approach.

In this system, the patient interacts with a robot through a computer game. The game and its parameters, e.g. number of repetitions, therapy duration, motion range, are set up according to exercises prescribed by a therapist, who also supports the whole procedure. When it is detected that the patient is not able to continue the wrist movement, the robot interacts gradually, further helping the patient to conclude the exercise. More detailed information on our rehabilitation system can be found in [26].

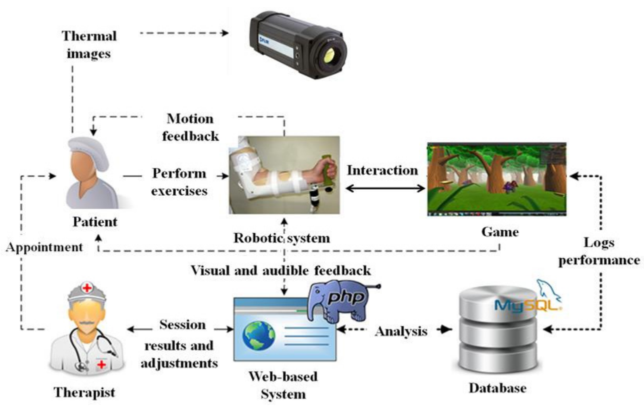

Figure 2. Overview of our rehabilitation robotic system. Note that the therapist may interfere in the game and robotic setup. Adapted from [26].

B. Thermal Image Camera

An infrared camera (FLIR A325sc, Gigabit Ethernet) was used to acquire the thermal images. This model has a sensitivity of 0.05°C at +30°C, ±2°C of reading accuracy, resolution of 320 × 240 pixels and 16-bit of dynamic range.

C. Database

For designing and evaluating the ANN, a database was created containing infrared thermal images of human faces corresponding to the emotions neutral, motivated and overstressed. The database availability on the web is under construction.

Thermal image acquisition was taken in an air conditioned room at temperature of 23±2ºC and 50% of humidity. Since the facial skin temperature is sensitive to the environment temperature [19], before recording the images the volunteers remained in resting conditions in the experimental room by approximately 10 min. The camera was located at the eyes level, approximately 1 m from the volunteer. A white cardboard panel was used as background for the image acquisition (Fig. 3).

Figure 3. Image capturing experimental environment.

The following stimulation techniques were adopted in order to induce the emotions under analysis. The motivated one was obtained from users watching some selected short comic videos (1-2min), in a procedure similar to that described by [28]. Individuals with happy expressions (Fig. 4) were considered motivated. On the other hand, neutral emotion corresponds to users exhibiting expression similar to the reference image shown in Fig. 4. Finally, the overstressed emotion was selected invoking a discomfort sensation by immersing one hand of the volunteer in a mixture of water and ice cubes inside a 2.5L vessel (temperature of 0ºC). The whole hand stayed in contact with the solution until the volunteer reported discomfort. In general, this sensation has occurred within one minute. The association of discomfort with low temperature water is a common procedure adopted by physiotherapists' community. The images were captured every second. This protocol produced the so-called evoked facial expressions.

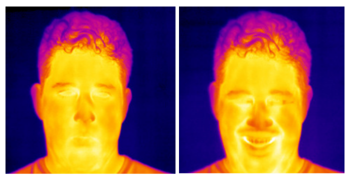

Figure 4. Examples of evoked facial expression for neutral (left) and happy(right).

Another image database was created during rehabilitation robotic therapy sessions by involving the same individuals as in the above-mentioned procedure. While the users interact with the rehabilitation robotic system through games, image acquisition occurred at one frame/s for every volunteer. This experimental setup generated what we called spontaneous emotions.

For every experimental scenario image sequences (taken by ThermaCAM Researcher Pro 2.10 software and saved in proprietary format .seq, FLIR) were recorded for the facial expressions (Neutral, Motivated, Overstressed).

Regardless the experimental scenario, the subjects were asked to stay in a comfortable position on the chair and to avoid head movement and also to fix their eyes on the computer screen. To minimize the impact of external stress factors and simultaneously establish a baseline in the thermal imagery, the volunteers stayed quiet into the experimental room before playing the game. This interval was necessary for the skin surface reaches a balanced thermal state under the room condition.

Data conversion was done by using the previously mentioned software. The original data extension (.seq) was converted into bitmap images (.bmp) and temperature matrix in Celsius degrees (.mat) of 240×320 pixels in size.

D. Image Processing

Firstly, the temperature data ranging from 24.0°C to 37.5°C were converted into grayscale image. To maximize the contribution of the thermal points in the analysis, the contrast of the image was enhanced.

To reduce the effect of the background pixels, the region corresponding to the face was automatically detected by a segmentation method for thermal images [29]. Concisely, this method detects the geometric coordinates of a rectangle circumscribed in the face by generating initially a binary version of the original image using the Otsu´s method [30]. The vertical projection of this binary image yields the upper limit (y_1) of the face, whereas the remaining image is horizontally divided into two parts and the horizontal projection is calculated by using the first part. This is necessary to determine the left (x_1) and the right (x_2) limits of the face. Finally, the lower limit ($y_2=y_1+(x_2-x_1)\times1.618$) is calculated through a golden ratio (Fig. 5).

After the face has been segmented, the subsequent phase consists of dividing the face into four different regions of interest (ROIs), including the forehead, the eyes, the nose and the mouth (Fig. 5). The metric used here to divide the face is as follows:

$$h2 = y1 + ((y2 - y1)/2) \quad (1)$$
$$y3 = y1 + (h2 \times 2/5) \quad (2)$$
$$y4 = h2 - (h2 \times 2/5) \quad (3)$$
$$y45 = h2 + (h2 \times 1/7) \quad (4)$$
$$y5 = y1 + ((y2 - y1) \times 0.7) \quad (5)$$
$$y6 = y1 + ((y2 - y1) \times 0.85) \quad (6)$$

where y1 and y2 are computed by the segmentation method [30] and h2 is the middle line of the face.

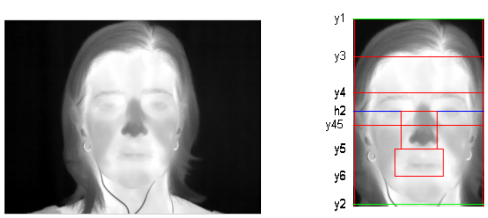

Figure 5. Temperature matrix converted into grayscale image (left) and segmented face divided into four blocks,depicted by red lines (right).

E. Feature extraction

To quantify the thermal patterns associated with the face sub-regions, two attributes (variance and entropy) were computed from the temperature matrix previously converted into a normalized grayscale image.

The definition of entropy E [bits/pixel] of an image is given as follows [31]:

$$E = -\sum P(i).log_2[P(i)] \quad (7)$$

where P contains the pixel histogram counts and i runs over all 256 (8-bit) gray values present in the image.

The local gray variance [intensity^2] of an image describes the deviation of the image gray values regarding the average gray level [31]:

$$\sigma^2 = \frac{\sum(gray\_value - average)^2}{number\ of\ pixels - 1} \quad (8)$$

where average is calculated by adding the gray intensities and then dividing the total by the number of pixels.

The entropy and the standard deviation (variance) were obtained from the average of all local entropy and variance values, respectively, computed in the 5×5 pixel-neighborhoods inside every region of interest (Fig. 5).

F. Classifier

A supervised three-layer feedforward ANN was designed and evaluated to work as a classifier. The ANN architecture is formed by eight inputs (one variance-entropy pair for every ROI) and three binary outputs were used to classify expressions into Neutral, Motivated and Overstressed.

The network has a single hidden layer and sigmoidal activation functions. Linear transfer function was adopted at the output layer. Backpropagation (Levenberg-Marquardt) was chosen as learning algorithm. The number of hidden neurons for an input layer with N neurons was estimated as $2N+1$ [32]. The database was divided into a training subset containing 70% of randomly selected images, 15% for validation and 15% for testing. The value of each input variable was normalized to [0 1]. The mean squared error (MSE) was used as stopping criterion and the maximum training epoch was set to 1000.

III. Results

For evaluating the face recognition accuracy of the present method, image sequences of neutral, motivated and overstressed faces of male and female subjects were collected. A set of representative thermal images is shown in Fig. 6.

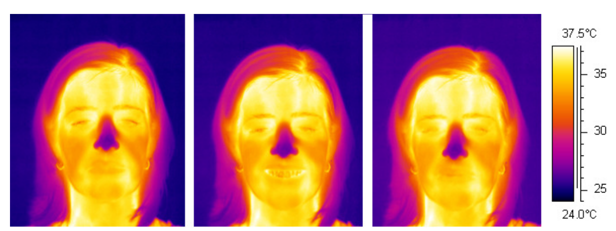

Figure 6. Representative set of infrared thermal images corresponding to spontaneous facial expressions. From the left to the right: Neutral, Motivated, and Overstressed. The vertical bar represents the temperature.

The experiments were conducted with 8 healthy volunteers. Excluding research groups that have large database (>100) [33], and (30) [34], the number of individuals in our experiment is comparable with most works on the field [10], [11], [15], [17], and [35].

The expressions were manually evaluated by the first and second authors. Subjects with closed eyes and with the face in an unsuitable position were excluded from the database. The total number of samples selected is shown in Table I.

The inputs in Table II summarize the information contained in the face sub-regions on the basis of first order statistics.

TABLE I. DATABASE USED IN THE EXPERIMENT. THE TOTAL AMOUNT OF IMAGES CORRESPONDS TO EVOKED AND SPONTANEOUS EXPRESSIONS.

	Facial expression		
Volunteer	***Neutral***	***Motivated***	***Overstressed***
V1	71	92	70
V2	101	174	60
V3	106	185	97
V4	83	86	111
V5	74	50	57
V6	106	85	160
V7	86	137	102
V8	125	121	106

TABLE II. MEAN ± SD OF ENTROPY AND VARIANCE FOR DIFFERENT FACIAL SUB-REGIONS AND FOR THE THREE EXPRESSIONS.

		Neutral	**Motivated**	**Overstressed**
Entropy [bits/pixel]	***Forehead***	3.09±0.25	3.11±0.26	3.14±0.32
	Eyes	3.95±0.13	3.97±0.17	3.99±0.14
	Nose	3.82±0.33	3.90±0.32	3.96±0.32
	Mouth	3.72±0.38	3.84±0.32	3.80±0.33
Variance [intensity^2]	***Forehead***	0.03±0.04	0.03±0.03	0.02±0.04
	Eyes	0.09±0.02	0.08±0.03	0.09±0.02
	Nose	0.07±0.06	0.07±0.06	0.09±0.05
	Mouth	0.04±0.04	0.05±0.04	0.04±0.05

A. *Data analysis*

In order to evaluate the effectiveness of the features in the different facial regions, an Analysis of Variance (ANOVA) was applied on the thermal data.

Data was initially grouped according to the area on the face, as it would only make sense to compare values for the same face area. ANOVA indicates that the volunteer group means for entropy and variance are statistically different (all *p*-values under 0.0001) and there is high correlation ($R^2 > 0.70$) between the values for both entropy and variance and volunteer, as shown in Table III. This reveals that the experiment has captured the thermal like-signature associated to every individual, as reported, e.g. by [36].

TABLE III. R-SQUARED VALUES OF ENTROPY AND VARIANCE VS. VOLUNTEER.

	Eyes	**Forehead**	**Mouth**	**Nose**
R^2 for entropy	0.885	0.766	0.872	0.936
R^2 for variance	0.849	0.912	0.794	0.959

As a way of eliminating the difference due to the individual thermal signature, one volunteer (#4) was selected and values for the spontaneous dataset were treated. Distinction on the Neutral, Motivated, and Overstressed groups can be visually noticed in the charts (Fig. 7).

For every face area (eyes, forehead, mouth and nose), the samples for entropy and variance, grouped by selected expressions, were tested.

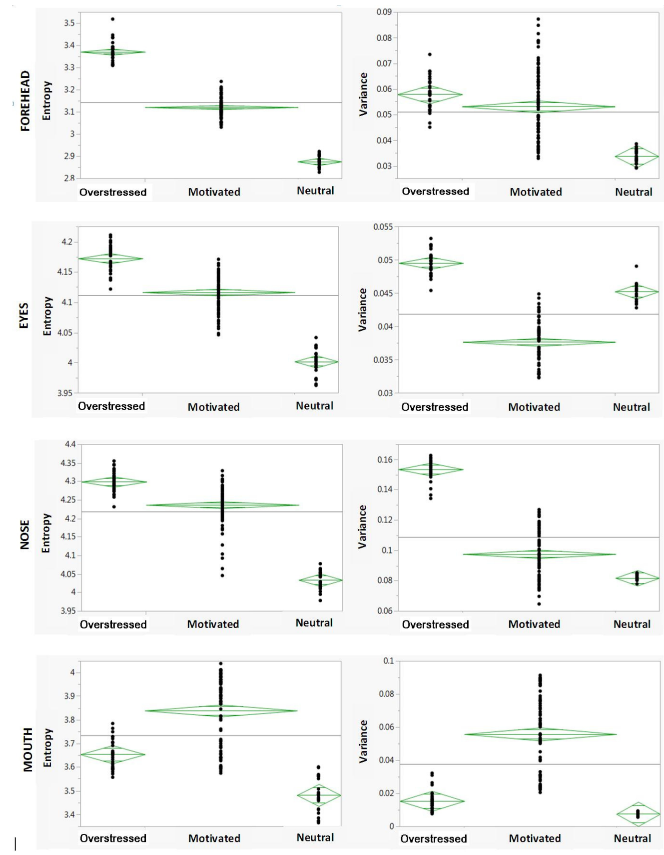

Figure 7. Entropy and variance vs. emotions by face region.

Eyes: high correlation between the expressions and the entropy ($R^2 = 0.823$); as shown in Table IV, and high correlation between the expressions and the variance ($R^2 = 0.783$).

Forehead: high correlation between the expressions and the entropy ($R^2 = 0.938$), and low correlation between the expressions and the variance ($R^2 = 0.353$).

Mouth: moderated correlation for both entropy ($R^2 = 0.579$) and variance ($R^2 = 0.581$) and expressions.

Nose: high correlation between the expressions and the entropy ($R^2 = 0.807$); high correlation between the expressions and the variance ($R^2 = 0.810$).

Means for the three emotions are significantly different (*p*-value < 0.0001) for all analysis.

TABLE IV. R-SQUARED VALUES FOR ENTROPY AND VARIANCE VS. EXPRESSIONS, FOR VOLUNTEER #4, CONSIDERING THE SPONTANEOUS DATASET.

	Eyes	**Forehead**	**Mouth**	**Nose**
R^2 for entropy	0.823	0.938	0.579	0.807
R^2 for variance	0.783	0.353	0.581	0.810

Therefore, correlation is high for 'eyes', 'forehead' and 'nose' face regions, and moderate for 'mouth', considering entropy and variance as the response values.

B. Motivation estimate by an ANN

The current version of serious games developed in our laboratory has focused on wrist function rehabilitation. Consequently, only the side to side wrist movement, i.e. flexion/extension, is excited by selecting a game scenario where nuts fall from trees and must be grasped by the game character using a joystick as part of the one degree of freedom robot. The stimulating component was a target score to be reached within the playing time (3 min). Both parameters were chosen by a therapist.

In the case of occurring no interaction with the game, e.g. when no nuts are falling, neutral expression is determined. Inherent to the wrist rehabilitation purpose, the coordinate where the fruit starts falling changes randomly. As the game proceeds and the user grasps more nuts aiming to reach the target score, a happy expression can be accounted as motivated. Finally, it was assumed that the overstressed expression occurred when the external stimulus (water with ice) was applied to evoke discomfort.

The first motivation measurement was based on neutral and motivated evoked emotions. For this purpose, a database of 794 images was divided into a training subset containing 556 images (70%) randomly selected, 119 images (15%) for validation and 119 images (15%) for testing. Table V summarizes the ANN recognition accuracy.

TABLE V. TESTING CONFUSION MATRIX INVOLVING NEUTRAL AND MOTIVATED EVOKED EXPRESSIONS. 17 HIDDEN NEURONS. VALIDATION MSE = 0.0001 AT 18^{TH} EPOCH.

	ANN classification	
Target expression	***Neutral***	***Motivated***
Neutral	45 (37.8%)	0 (0.0%)
Motivated	1 (0.8%)	73 (61.3%)

According to these results, the expressions correctly classified into neutral and motivated enumerate an overall performance of 99.2%.

When the expression corresponding to overstressed was included in the analysis, the overall performance of the ANN has reduced slightly (97.3%) (Table VI). For this case, a database containing, respectively, 346 (27.7%), 540 (43.2%) and 364 (29.1%) of neutral, motivated, and overstressed images was randomly divided into 875 (training), 187 (validation) and 187 (testing).

TABLE VI. TESTING CONFUSION MATRIX INVOLVING NEUTRAL, MOTIVATED AND OVERSTRESSED EVOKED EXPRESSIONS. 17 HIDDEN NEURONS. VALIDATION MSE = 0.009 AT 18^{TH} EPOCH.

	ANN classification		
Target expression	***Neutral***	***Motivated***	***Overstressed***
Neutral	51 (27.1%)	2 (1.1%)	0 (0%)
Motivated	2 (1.1%)	84 (44.7%)	0 (0.0%)
Overstressed	0 (0%)	1 (0.5%)	48 (25.5%)

Finally, table VII shows the ANN performance (92.6%) on a database formed by images of evoked and spontaneous reactions for the three facial expressions. A database consisting of 2445 images, 752 (30.8%) neutral, 930 (38.0%) motivated and 763 (31.2%) overstressed, was evaluated by randomly selecting 1711 (training), 367 (validation), and 367 (testing) images.

TABLE VII. TESTING CONFUSION MATRIX BY COMBINING NEUTRAL, MOTIVATED AND OVERSTRESSED EXPRESSIONS FOR BOTH EVOKED AND SPONTANEOUS REACTIONS. 17 HIDDEN NEURONS. VALIDATION MSE = 0.043 AT 20^{TH} EPOCH.

	ANN classification		
Target expression	***Neutral***	***Motivated***	***Overstressed***
Neutral	106 (28.9%)	2 (0.5%)	2 (0.5%)
Motivated	9 (2.5%)	132 (36%)	1 (0.3%)
Overstressed	0 (0.0%)	13 (3.5%)	102 (27.8%)

Despite the good correlation with manual assessments, Fig. 8 and 9 show a representative set of misclassified images.

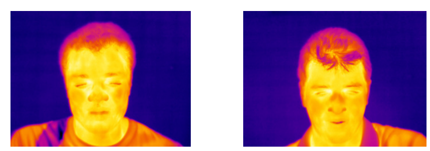

Figure 8. Examples of spontaneous overstressed expressions misclassified as motivated.

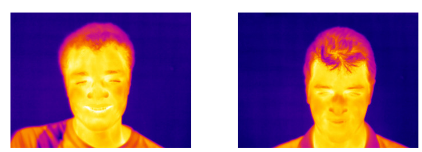

Figure 9. Examples of spontaneous motivated expressions misclassified as neutral.

IV. CONCLUSION

The information contained in thermal images of patients performing therapeutic exercises demonstrated to be useful to infer the degree of user engagement in the context of rehabilitation robotic with serious games. It is expected that the automatic detection of emotions in patients performing rehabilitation robotic therapy might positively influence the treatment regarding some performance parameters of the patient. According to the detected expression the game could, for instance, be online adjusted or even re-programmed aiming to maximize the experience of the patient. Future research direction focuses on a brain-machine interface capable of capturing and interpreting brain electrical signals and correlated them with thermal images.

ACKNOWLEDGMENT

The authors thank CAPEs for the financial support, the Research Center in Optics and Photonics (CePOF) for generously allowing use of the infrared thermal camera. We also would like to thank the volunteers for kindly participating on this study.

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