Negative emotion detection using EMG signal

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***Abstract*— Generally, Negative emotions can lead to health problems. In order to detect negative emotions, an advanced method of the EMG signal analysis is presented.**
Negative emotions of interest in this work are: fear, disgust and sadness. These emotions are induced with presentation of IAPS (International Affective Picture System) images.
The EMG signal is chosen to extract a set of characteristic parameters to be used for classification of emotions. The analysis of EMG signal is performed using the wavelet transform technique to extract characteristic parameters while the classification is performed using the SVM (Separator Vector Machine) technique. The results show a good recognition rates using these characteristic parameters.

Keywords— Negative emotions, EMG Signal, Pertinents parameters, Wavelet transfrom, SVM Classifier.

I. INTRODUCTION

Emotions are complex reactions that affect both body and mind. Generally, negative emotions were always linked to increases in health problems [1]. However, the mechanisms underlying the relationship between emotions and health are complex. But, it was found that chronic experience of negative feelings such as anxiety, sadness and fear expose people to suffer a variety of physical problems such as asthma, headaches, ulcers and heart disease [2].

The emotion is a psychophysiological process produced by the activity of the limbic system in response to a stimulus, which in turn causes activation of the somatosensory system [3].
In addition, various peripheral physiological changes are generated, and bodily feedback is necessary for the emergence of an emotion [4]. This theory can be illustrated briefly as follows.

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Stimulus → Physiological responses → Sensation of these peripheral changes → Emotion.

Based on work in psychology, some measures consider affective states as categories, others as a multidimensional construct.
First, emotions are considered as episodic and universal characteristics, but the second propose to model all emotional reactions with several dimensions [5]. The two most known dimensions are the valence (positive, negative) and activation (active, passive).
In our work, we base on three emotions that will be used for emotional recognition: fear, sadness and disgust. Below, we give the definitions of emotions of interest:
Fear: Dangerous situations or psychological harm put us in a stressful emotional state, often accompanied by physiological reactions.
Disgust: Loss of appetite or reluctance face to a substance, and more rarely a situation, resulting in a feeling of malaise.
Sadness is an emotion that informs us of the importance or the presence of an emotional need. It is even more intense if the loss is subjectively significant.
The experiment was conducted by researchers at LCOMS laboratory at Lorraine University in France. It involves collecting data consisting of EMG signal acquired by the Procomp equipment.

After acquisition and filtering EMG signals, some relevant parameters are extracted. Data classification is done by SVM technique (separator vector machine), using a multiclass SVM programs one against all [6], which will be suitable for our application. Also, a comparison of the three kernels: linear, polynomial and Gaussian is made.
The rest of this paper is organized as follows: In Section I, an introduction is given. Data collection of the EMG signal is described in section II. Section III presents the extraction of relevant parameters. Emotion recognition using SVM technique is presented in section IV. The results of our experience and discussion are given in Section V. Section VI gives a conclusion and future works.

II. PHYSIOLOGICAL DATA COLLECTION

A. Emotion Induction

The experiment was performed by researchers at LCOMS laboratory in Lorraine University. Five subjects aged from 25 to 28 years, have tried to test three affective states with an incentive system controlled by computer by passing IAPS (International Affective Picture System) images, which induces the expression of the three emotional states: fear, sadness, and disgust.

B. Electromyogramme Signal Acquisition

The EMG signal is the recording of electrical activity produced by the muscle fiber when the muscles contract. The emotional tone is an involuntary contraction, permanent and moderate of muscles. This slight tension is an expression of changes in negative emotions such as fear or mental stress [4].

It is shown that muscle activity increase during negative valence emotions [7]. According the above results, the EMG signal is considered in this work as a biomedical signal to be taken into account in determining the emotional state of the subject. This experiment consists in collecting data of EMG signals acquired by the Pro Comp hardware [8].

C. Measurement Principle

The positive and negative electrodes should be placed parallel to the muscle fibers. The ground electrode is to be placed on a neutral part, preferably at an equal distance from the other two electrodes.

Since all the muscle fibers contract at different rates, the signal detected by the sensor is the potential difference of constant variation between positive and negative electrodes. The number of muscles fibers during a contraction varies according to the strength required to perform the movement. Therefore, the intensity and the amplitude of the electrical signals are proportional to the contraction force. EMG signal is filtered by band pass optimal finite impulse response filter with a band pass frequency of [20-125] HZ [9].

The amplitude changes are directly proportional to muscle activity. Normal resting values are usually between 3 and 5 mV.

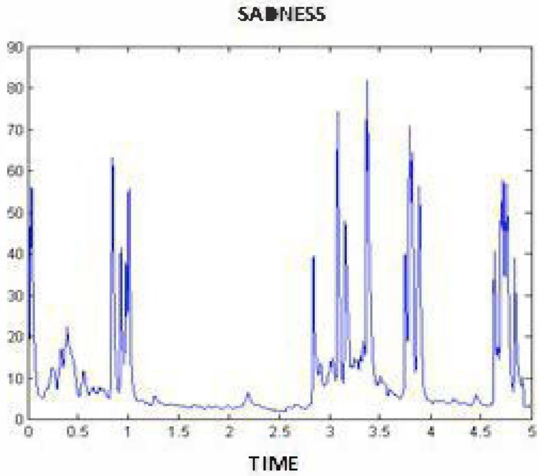

Fig 1. EMG signal for sadness emotion

III. FEATURE EXTRACTION

A. EMG signal Rectification

The rectification of the EMG signal is used to quantify depolarizations in all phases, ie the potential approaches or moves away from the electrode. So, the values are positive or negative.

$$\mathbf{EMG\_rect = abs(EMG)} \quad (1)$$

B. Quadratic mean

This parameter quantifies the energy on a time interval by calculating the root mean square. It is used to eliminate the variability due to the instantaneous excitation of muscle fibers. In fact, every emotion has corresponding activation energy. Indeed, fear energy is greater than sadness energy. Also, this later has energy which is greater than the disgust energy [10].

$$\mathbf{mean_{quad}} = \sqrt{\frac{1}{N}\sum_{i=0}^{N} \mathbf{EMG\_rect}_i^2} \quad (2)$$

N : samples number

C. Average Energy

This parameter quantifies the average energy of EMG signal, it can be changed with the emotional state and it is given in decibel.

So, the average energy is defined as follows:

$$\mathbf{mean_{energ}} = \mathbf{10\log_{10}}\left(\frac{1}{N}\sum_{i=1}^{N} \mathbf{10}^{\mathbf{EMG\_rect_i/10}}\right) \quad (3)$$

D. EMG Signal Intégration

EMG integration is calculated to quantify the average level excitation on time interval by integrating the rectified EMG.

$$\textbf{EMG\_integ}=\left(\sum_{n=1}^{N}\textbf{EMG\_rect(n)}\right)(1/f) \qquad (4)$$

f : Sampling frequency.

Figure 2 shows an example of EMG signal and integrated EMG signal.

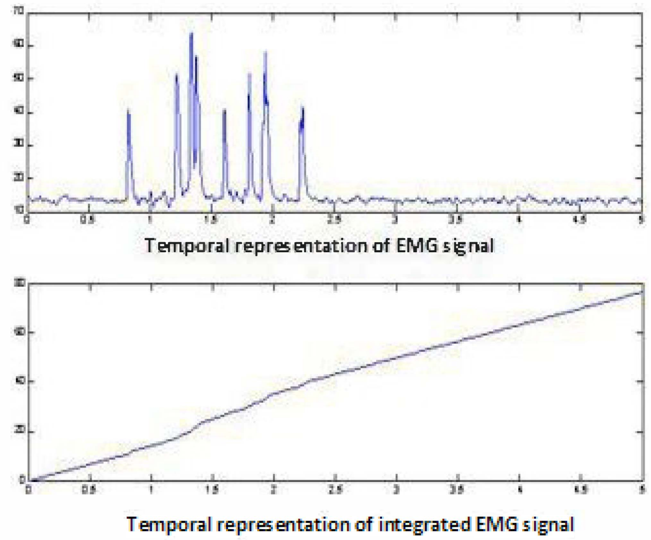

Fig 2. Temporal representation of EMG signal and integrated EMG

E. EMG signal Analysis by Wavelet

EMG signal is considered as instable signal [11], for this, we have used wavelet transform to analyze it.

The wavelet transform decomposes the signals through the dilated and translated wavelet. A wavelet is a function (mother wavelet) with zero mean value.

$$\int_{-\infty}^{+\infty} \boldsymbol{\psi}(\mathbf{t})\mathbf{dt} = \mathbf{0} \qquad (5)$$

It is also normalized and centered.

$\|\boldsymbol{\psi}\|$=**1** and centered at **t**=0

A time-frequency atom family is obtained by dilatation by **a** and translation by **b**.

$$\boldsymbol{\psi}_{\mathbf{a,b}}(\mathbf{t})=\frac{1}{\sqrt{|a|}}\,\boldsymbol{\psi}\left(\frac{t-b}{a}\right) \qquad (6)$$

The wavelet transform of the function f(t) is given by this equation [12] :

$$\mathbf{Wf}\ (\mathbf{a,b})=<\mathbf{f}, \boldsymbol{\psi}_{\mathbf{a,b}}>=\int_{-\infty}^{+\infty} \boldsymbol{\psi}_{\mathbf{a,b}}(\mathbf{t})\ \mathbf{f}\ (\mathbf{t})\ \mathbf{dt} \qquad (7)$$

Applying Daubechis window level 5 (db5), the EMG signals is decomposed into approximations **A** and details **D** [13].

After extracting coefficients **D** (**D1** to **D6**) and **A** (**A1-A6**), the maximum and the minimum for each coefficient is calculated. However details describe well high valences and high activations of the autonomic nervous system. But approximations correspond to low activations and low emotional valences.

Then, **Max** and **Min** of the wavelet coefficients (presented in fig 3 and fig 4) are relevant parameters that we want to classify using the SVM technique.

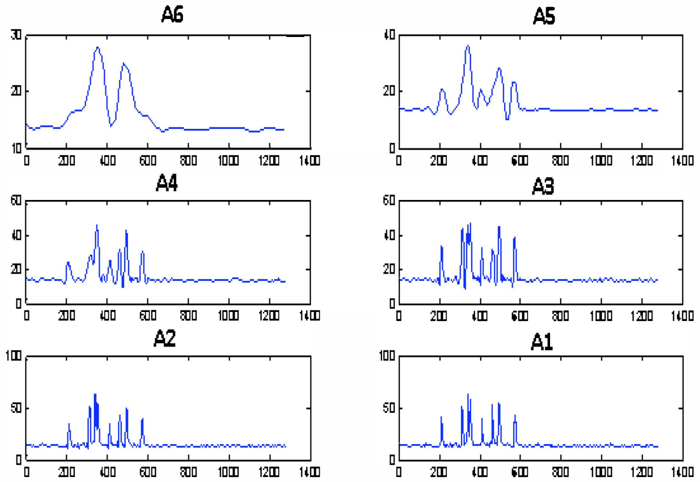

Fig 3. Approximation coefficients for disgust emotion

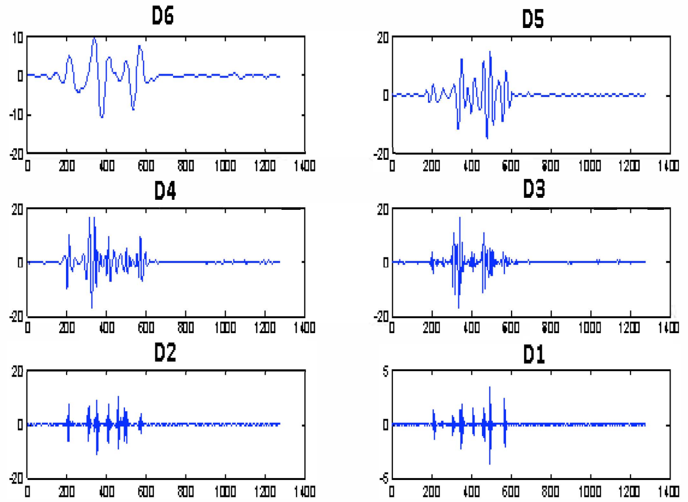

Fig 4. Detail coefficients for disgust emotion

IV. EMOTION CLASSIFICATION METHOD

The support vector machine (SVM) method is a binary classification technique by supervised learning [14].

The aim is to learn the **h(x)** function through a training set given below:

$$\{(x_1, l_1), (x_2, l_2) \ldots\ldots (x_p, l_p)\} \in R^N \times \{-1,1\} \quad (8)$$

Where l_k are the labels, x_k are input vectors, being in a space R^N and **p** is the size of the training set.

The technique seeks a separating hyperplane $h(x) = wx + w_0$ which minimises the number of errors through the introduction of variable spring ξ_k, which can relax the constraints on the training vectors[15].

$$l_k(w\, x_k + w_0) \geq 1 - \xi_k, \xi_k > 0, \quad 1 \leq k \leq p \quad (9)$$

With the previous constraints, the optimization problem is modified by a penalty term which penalizes high variables, spring ξ_k:

$$\text{Minimise} \frac{1}{2}||w||^2 + C\sum_{k=1}^{p} \xi_k, \quad C > 0 \quad (10)$$

Where **C** is a constant that controls the compromise between the number of classification errors and the margin width.

The three kernel function and its parameter are mentioned below [16].

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A. Linear kernel

$$K(x_i, x_j) = x_i . x_j \quad (11)$$

B. Polynomial kernel

$$K(x_i, x_j) = (x_i . x_j + c)^n \quad (12)$$

n : degree

C. Gaussian kernel

$$K(x_i, x_j) = \exp\left(\frac{||x_i - x_j||^2}{\sigma^2}\right) \quad (13)$$

σ : standard deviation

The SVM method is applicable for binary classification tasks, but there are extensions to the multiclass classification [17].

Formally, the training and testing samples can be ordered here in M classes $\{C_1, C_2, \ldots, C_M\}$

The one against all method consist of constructing **M** binary classifiers by assigning the label 1 to samples of one class and the label -1 to all others [17].

In the test phase, the classifier, which gives the highest margin, wins the vote.

$$\text{Class of } x = \operatorname{argmax}_{x_k}(h_k(x)),\ k \in \{1, \ldots, M\} \quad (14)$$

Data classification is done using one against all SVM multiclass programs, which will be adapted to our application and considering the three kernels.

In this evaluation, for each emotion considered, six samples are used for training and for samples for test. Recognition rates are calculated for different subjects, using three kernels: linear, polynomial (for different degrees n) and Gaussian (for different standard deviation values σ) of the SVM method.

The following tables (Table 1 to Table 5) represent the overall recognition rates:

V. RESULTS AND DISCUSSIONS

	Linear	poly		Gauss					
	n=1	n=2	n=3	σ =5	σ =10	σ =15	σ =20	σ =25	σ =35
Recog rate	54.55%	54.55%	59.09%	50%	59.09%	63.64%	72.73%	77.27%	**81.82%**

TABLE 1. Recognition rates for subject 1

	lineair	poly			gauss				
	n=1	n=2	n=3	σ =5	σ =10	σ =15	σ = 20	σ =25	σ =35
Recog rate	38.10%	42.86%	42.86%	**57.14%**	46.75%	47.62%	47.62%	47.62%	52.38%

TABLE 2. Recognition rates for subject 2

	lineair	poly		gauss					
	n=1	n=2	n=3	σ =5	σ =10	σ =15	σ =20	σ =25	σ =35
Recog rate	33.33%	9.52%	9.52%	14.29%	28.57%	33.33%	28.57%	**47.62%**	46.35%

TABLE 3. Recognition rates for subject 3

	lineair	poly			gauss				
	n=1	n=2	n=3	σ =5	σ =10	σ =15	σ = 20	σ =25	σ =35
Recog rate	31.82%	45.45%	45.45%	36.36%	66.66%	72.73%	**77.27%**	77.27%	70%

TABLE 4. Recognition rates for subject 4

	lineair	poly		gauss					
	n=1	n=2	n=3	σ =5	σ =10	σ =15	σ =20	σ = 25	σ =35
Recog rate	36.3%	35%	35%	35.5%	36%	40%	36.36%	**45.45%**	44.35%

TABLE 5. Recognition rates for subject 5

We note that for all subjects, Gaussian kernel generate improved recognition rates compared to those found using the linear and polynomial kernels. This means that the relevant parameters extracted from the EMG signal are inseparable.

Also, we observe that when the value of the standard deviation σ increases, recognition rates increase.

For subjects 1, it reached the maximum recognition rate for σ = 35. But, for the subject 2 the best recognition rate is found for σ = 5.Thus, for subjects 3 and 5 we reached the maximum recognition rate for σ = 25. Also, for subject 4, we found the maximum recognition rate when σ = 20.

Using the Gaussian kernel, and fixing σ = 35, the following study concerns the extraction of recognition rates for each negative emotion. However, the three negative emotions which are: fear, disgust and sadness have different levels of activations and valences.

For all subjects, the recognition rate of each emotion are calculated and shown in tables below:

	fear	disgust	sadness
Recognition rate	**65%**	55%	60%

TABLE 6. Recognition rates for subject 1

	fear	disgust	sadness
Recognition rate	**70%**	60%	68%

TABLE 7. Recognition rates for subject 2

	fear	disgust	sadness
Recognition rate	**64%**	57%	61%

TABLE 8. Recognition rates for subject 3

	fear	disgust	sadness
Recognition rate	**62%**	54%	58%

TABLE 9. Recognition rates for subject 4

	fear	disgust	sadness
Recognition rate	**63%**	57%	58%

TABLE 10. Recognition rates for subject 5

According to these tables, we remark that fear is well detected compared to sadness. And the latter, is well recognized compared to the disgust emotion.

Indeed, the fear has greater valence and activation relative to other emotions.

So we can say that relevant parameters extracted from the EMG signal describe well these negative emotions, especially, those with high activations and high valences levels.

Also, the Gaussian kernel of SVM technique provides good recognition rates.

VI. CONCLUSION

In this paper, an approach of negative emotions recognition has been proposed, studied and evaluated. This approach is based on the analysis and processing of EMG signal, for the recognition of three negative emotions, which are: sadness, disgust and fear, using wavelet transform.

Relevant parameters extracted from the EMG signal, describe well negative emotions with high activations and high valences. Also, the Gaussian kernel and the one against all method of SVM technique which is applied in our approach have shown its reliability and performance for the classification of three emotions.

As a future work, we intend to find a more efficient inductor and to study its influence on emotion recognition. We plane also, to incorporate other means of emotion recognition such as speech recognition.

REFERENCES

[1] Chun-Han Yang "Negative emotion detection using the heart rate recovery and time for twelve-beats heart rate decay after exercise stress test" International Conference on Neural Networks (ICNN) . 2010.p 2-4.

[2] N. Khetrapal "Detection of Negative Emotions in Autistics: Questioning the 'Amygdala Hypothesis'". The New School Psychology Bulletin Vol. 5, No. 2, 2007.

[3] C. Lalanne "cognition: Cognitive neuroscience approach "Report, Department of Computer Science., René Descartes University, Paris, France. 2005. pp. 26-28

[4] A. Rivière, B. Godet "Affective Computing: Adaptive role of emotions in human Machine interaction" Report , Charles de Gaulle university,

[5] S Anders , M Lotze , M Erb , W Grodd , N Birbaumer "Brain activity underlying emotional valence and arousal: a response-related fMRI study". Institute of Medical Psychology and Behavioral Neurobiology, University of Tübingen, Tübingen, Germany. PubMed publication.

[6] A. Rakotomamonjy " SVM and Kernel Methods Matlab " , 2005M.

[7] Guiose " Fondements théoriques et techniques de la relaxation" Rapport, medicine Faculty de, Paris-VI university, November 2003. pp. 21-23.

[8] Thought Technology "Guide of ProComp Infiniti device" Montréal, Canada. 2003.

[9] C. ToweBruce "Standard Handbook of Biomedical Engineering and Design " Standard handbook, Digital Engineering Library, MCGRAW-HILL, Part 4, Bioelectricity,Chapter 17 Bioelectricity And Its Measurement, Arizona State University, Tempe, Arizona, 2004. p 26-43. www.digitalengineeringlibrary.com

[10] S. Narayanan, R. Pieraccini, "Recognition of negative emotions from the speech signal". Univ. of Southern California, Los Angeles, CA, USA. Automatic Speech Recognition and Understanding, 2001. ASRU '01. IEEE Workshop. pp 240-243

[11] Bo Cheng, Liu Guangyuan "Emotion Recognition from Surface EMG Signal Using Wavelet Transform and Neural Network". Bioinformatics and Biomedical Engineering, 2008. ICBBE 2008. The 2nd International Conference. p 1363

[12] P. Gaillard, R. Lengellé "Signal processing and analysis" Ellipes edition, p 110; 257; 185, 2006.

[13] M. Rizon "Discrete Wavelet Transform Based Classification of Human Emotions Using Electroencephalogram Signals", the American Journal of Applied Sciences 7 (7): 878-885, 2010.

[14] H. Mohamadally, F. Boris, " SVM : separator vector machine ". Report, January, 2006.

[15] J.P. Asselin, F.Z. Kettaf, " Theoretical basis for learning and decision pattern recognition of form". Cedadues edition.2005

[16] A. Cornuéjols, " A new method of learning: The separator vector machine " report, Orsay University, France, 2002.pp.18-22.

[17] Chihwei Hsu and Chih-Jen Lin, " A comparison of methods for multi class support vector machines ". IEEE Transactions on Neural Networks, 2002. pp.415–425.

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