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CONTACTLESS MEASUREMENT OF MUSCLES FATIGUE BY TRACKING FACIAL FEATURE POINTS IN A VIDEO

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ABSTRACT

Physical exercise may result in muscle tiredness which is known as muscle fatigue. This occurs when the muscles cannot exert normal force, or when more than normal effort is required. Fatigue is a vital sign, for example, for therapists to assess their patient's progress or to change their exercises when the level of the fatigue might be dangerous for the patients. The current technology for measuring tiredness, like Electromyography (EMG), requires installing some sensors on the body. In some applications, like remote patient monitoring, this however might not be possible. To deal with such cases, in this paper we present a contactless method based on computer vision techniques to measure tiredness by detecting, tracking, and analyzing some facial feature points during the exercise. Experimental results on several test subjects and comparing them against ground truth data show that the proposed system can properly find the temporal point of tiredness of the muscles when the test subjects are doing physical exercises.

***Index Terms*—** Fatigue, Facial Feature Detection and Tracking, Tiredness, Electromyography

1. INTRODUCTION

Fatigue is defined as feeling weakness. It is referred to as tiredness and exhaustion. It causes temporary inability in maintaining optimal cognitive or muscle performance. Fatigue can be mental or physical [1, 2]. In mental fatigue, patients cannot concentrate on a problem or cannot perform their daily activities as easy as they used to. But in physical fatigue, person's muscle feels weakness. Muscle fatigue impairs the normal performance capacity of the muscles as it takes more energy than normal case to achieve a desired performance. For instance, when you lift a very heavy weight or you hold your muscles in one position for a long time (called isometric contraction [3]), muscles get tired.

Physical or muscles fatigue is an important sign, for instance, for therapists for taking care of patient's progress. Based on such monitoring of patients, therapists can change the exercise, make it is easier or even stop it when the level of fatigue goes beyond a level that might be harmful for the patient. Nowadays, measuring muscle fatigue is usually done by a direct contact between the muscles and a sensor. Such sensors can be a force gauge, EMG electrodes, Mechanomyogram (MMG) sensors. Measuring the fatigue using a force gauge is very easy. But, it requires some devices like a hand grip dynamometer [4]. It, hence, is impossible to measure the fatigue using this method for an exercise using, for example, dumbbells. The EMG method uses electrodes to detect electrical current when muscles are contracted [5]. EMG can record signals from muscles, which can be accomplished using two approaches know as invasive (needle electrode-based) and non-invasive (skin surface electrode-based). The non-invasive one which is also known as surface EMG (sEMG) is popular for collecting signals from muscle fatigues [6]. This technique has been used very often [7-11], though it is complex to implement, particularly in automatic fatigue detection. EMG signal is very sensitive to noise which generally should be filtered. It also requires wearing adhesive gel patches that may cause skin irritation and slight pain. The (MMG) is another non-invasive method for assessing of muscle fatigue which is often used with EMG technique. EMG records electrical signals, but, MMG captures mechanical signals generated from muscle contraction. Similar to EMG and other fatigue detecting techniques, the sensors applied in MMG, such as accelerometer, goniometer and microphone [12-14] require direct skin contact. MMG cannot be used for dynamic contraction. Moreover, they are expensive and physically balkier. Furthermore, MMG, similar to EMG, is sensitive to noise [5].

To overcome the problems of contact-based methods of muscle fatigue measurement, in this paper, we develop a contactless computer vision technique. The proposed method is based on the work of [15-17] which show that heartbeat rate can be measured from facial images. The point here is that blood circulation to the head makes some periodic movements on the face which are not visible to the naked eyes, but can be revealed by video magnification [18] to measure the heartbeat rate. We have extended the same concept to muscle fatigue measurement. We utilize this fact that the energy that is released from shaking of muscles (due to tiredness) results in shaking of the face which might not always be detected by naked eyes, but can be well

discovered by computer vision techniques similar to those of [15, 16]. This actually makes good sense because any motion or any contraction during muscles activity happens by a group of motor units (including motor neuron and the skeletal muscle fibers). When a muscle is fatigued, some of the motor units drop out of service and leading to muscle's shaking status which consequently results in shacking of the face. To the best of our knowledge, there is not any similar previous works on detecting muscle fatigue using computer vision techniques.

The rest of this paper is organized as follows: Section 2 presents the details of the proposed approach for detecting muscle fatigue. Experimental results and performance evaluation of the proposed system are discussed in Section 3. Finally, conclusions are drawn in Section 4.

2. THE PROPOSED SYSTEM

As mentioned earlier, muscles start shaking after they get tired due to an activity. This shaking gets reflected on the face. This is exactly the purpose of this paper to detect this shaking by analyzing facial image and tracking specific facial features for measuring the muscles fatigue. The block diagram of the proposed system is shown in Figure 1. First a camera (a Logitech webcam) is continuously filming the subject with a resolution of 640x480 pixels. Then, the subject's face is detected by Viola and Jones [19] face detector. Then, we extract and track some of the facial feature points. Thereafter, we extract muscle fatigue-related vibration signal of the head by removing large head motion using a moving average from the trajectories of the chosen facial features [15]. Afterwards, the extracted vibrating signal is segmented and filtered using a pass band filter to calculate the released energy from the vibrating signal. Before filtering, to enhance the coherency between the blocks (segmented sequences) and decreasing windowing effects, 75% overlapping with Hamming window is utilized. Then, we calculate the power spectral density to obtain the energy that is released due to shaking of the face to finally index the fatigue. These are explained in the following subsections.

2.1. Trajectory generation

From the detected faces by Viola and Jones face detector [19] we extract the facial regions of interest using the method of [15]. These regions contain stable facial feature points which are those points that are not sensitive to changes in facial expressions. These facial features points are chosen and then tracked over time by [20] to generate facial feature trajectories. Then, we only keep those trajectories which their displacements in any two consecutive frames are not larger than a predefined threshold.

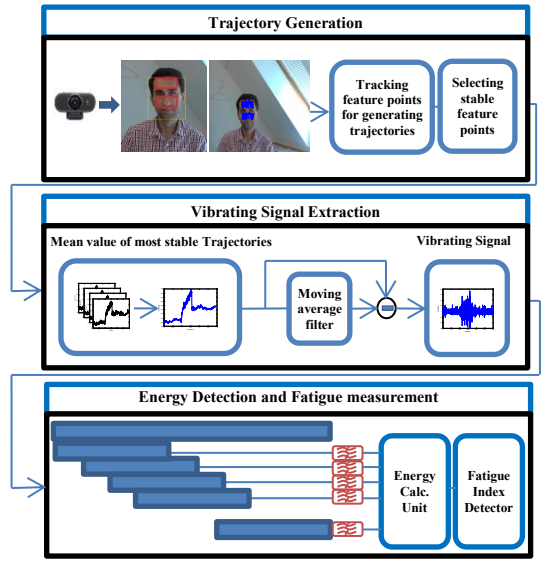


Figure 1: The block diagram of the proposed system

2.2 Muscle fatigue-related vibrating signal extraction

The chosen trajectories in the previous step are used to extract muscle fatigue-related vibrating signal. The trajectories are usually noisy due to, for example, error in feature tracking and any unwanted muscle motion like facial expression. To reduce the effect of such noises we use a mean filter. To do so, we use:

$$T(n) = \frac{1}{M}\sum_{m=1}^{M}(y_m(n) - \bar{y}_m) \qquad (1)$$

where $T(n)$ is the shifted mean filtered trajectory, $y_m(n)$ is the n_{th} frame of the trajectory m, M is the number of the trajectories, N is the number of the frames in each trajectory and $\bar{y}_m$ is the mean value of the trajectory m, which is given by:

$$\bar{y}_m = \frac{1}{N}\sum_{n=1}^{N} y_m(n) \qquad (2)$$

Then, the vibrating signal $V_s(n)$ which carries the shaking information of is obtained by:

$$V_s(n) = T(n) - \frac{1}{R}.\sum_{r=0}^{R-1} T(n-r) \qquad (3)$$

where R is the number of points involved in the averaging (here we use the experimentally obtained value of 35).

2.3 Energy measurement and fatigue detection

To measure the released energy of the muscles we need to segment the trajectories (with length t_{sec} to small time blocks with Δt_{sec} length). Segmenting the trajectories help us to measure the fatigue in the steps of time. After windowing, each block is filtered by a pass band ideal filter with cut off frequency interval of [3-5] Hz. Figure 2 shows the power of

the filtered vibrating signal with cut off frequency interval of [3-5] Hz. We observe that the power of the signal rises up when the fatigue happens (interval of [127–185]).

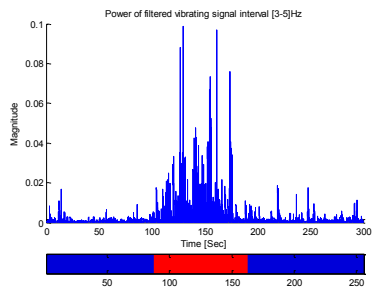


Figure 2: Power of the trajectory during fatigue test: The Blue regions are the resting time and the red region shows the fatigue due to exercise.

After filtering, the energy of i_{th} block, E_i, is calculated as:

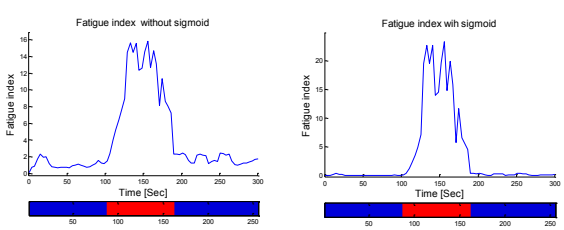
$$Ei = \sum_{j=1}^{M} \left|Y_{ij}\right|^2 \quad (4)$$

in which, E_i is the calculated energy of the i_{th} block, Y_{ij} is the Fast Fourier Transform (FFT) of the trajectories and M the is length of Y. Finally, fatigue occurrence is found by:

$$F_i = k \frac{E_i}{\frac{1}{N}\sum_{j=1}^{N} E_j} \tanh\left(\gamma \frac{E_i}{\frac{1}{N}\sum_{j=1}^{N} E_j} - 1\right) \quad (5)$$

in which, F_i is the fatigue index, E_i is the calculated energy of the i_{th} block, N is the number of the initial blocks in the normal case (before starting the fatigue), K is the amplitude factor, and γ is a slope factor.

It can be seen that in Eq. (5) a bipolar sigmoid (tangent hyperbolic) has been applied to E_i (the calculated energy). This actually suppresses the fake peaks that appear in the results because of the facial expression and the volunteer motions. Figure 3 illustrates the effect of the sigmoid function on the output results. Experimentally, we got reasonable results with k = 10 and γ = 0.01.



(a) (b)

Figure 3: Comparing the output without using sigmoid (a) and with using sigmoid (b). The blue regions are the resting time and the red region is the fatigue due to exercise.

3. EXPERIMENTAL RESULTS

The proposed system has been implemented in Matlab R2013a. The test subjects participating in evaluation of the system were filmed by two webcams: one was filming the frontal views of the face and the other one filming the full body of the test subjects, for manual verification of the synchronized shaking of arms and faces of the test subjects during the experiments.

There were 20 persons involved in the testing, 14 in one testing scenario and six in another testing scenario. The two testing scenarios evaluated the system in two different fatigue detection exercises known as maximal muscle activity and submaximal muscles activity [21]. These tests which are explained in the following scenarios are usually used in detecting muscle fatigue [4].

3.1 Testing scenario 1 (maximal muscle activity)

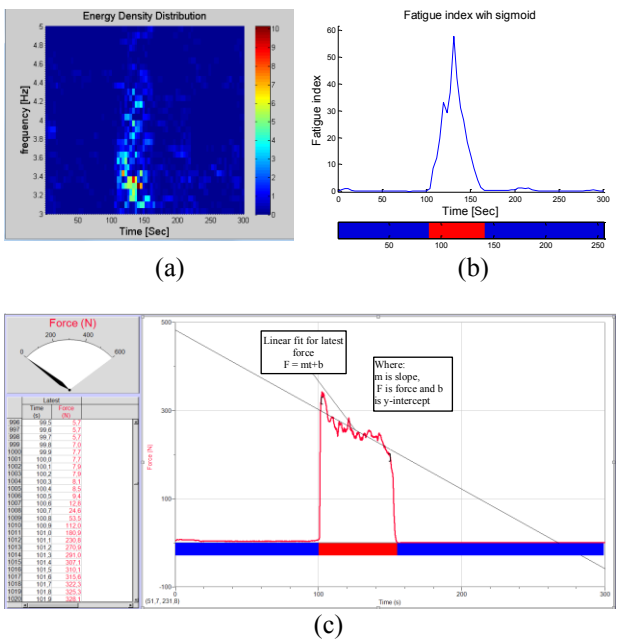
In this scenario we have considered the proposed algorithm's accuracy in maximal muscle activity. For validating our results, we utilized a hand grip dynamometer to produce ground truth data by analyzing the recorded data. We asked the test subjects to squeeze the device as much as they can while they were looking at the webcam which was filming their faces. Next, the data obtained by the proposed system was compared against the one recorded by the dynamometer. Table 1 compares the duration of the fatigue detected by the proposed system and the dynamometer.

Figure 4(a) graphically depicts the amount of the energy which is released in each time block during for one of the test subjects. Vertical axis of this figure shows the released energy in the frequency domain. According to the figure, the regions with blue color correspond to the durations that subjects are resting or doing exercise without fatigue. During the fatigue, depending on the level of subject's fatigue, the color is respectively changing to light blue, yellow, orange, and finally red. This figure actually shows the distribution of the Energy Spectral Density (ESD) in the frequency domain in the interval of [3-5] Hz, where the colors on the map depict the locations of strong variation components of $V_s(n)$.

Using this information, not only we can approximate the fatigue, but we can see which components carry most of the shaking energy due to the fatigue. However, for detecting the fatigue it is better to use a line graph like the one shown in Figure 4(b) wherein the boundaries between the fatigue and the rest areas are clearly visible. Fatigue in this figure happens when the fatigue index sharply goes beyond the threshold. It seems that the ideal value of the threshold is zero, but based on our experience it should be a bit larger than zero to remove fake peaks due to unwanted motions. However, selecting larger thresholds decrease the accuracy of the fatigue duration. Figure 4(c) shows the recorded data using the dynamometer. The part of the graph with a falling force indicates the fatigue region. It can be seen from these figures and also from Table 1 that there is a good agreement between the results of the proposed system and the ground truth.

Table 1: Comparing the fatigue durations obtained by the proposed system against those obtained by the dynamometer in Testing Scenario 1.

Subjects	Ground truth by the dynamometer (sec.)	Fatigue duration by the proposed system (Sec.)
Subject 1	103.7 - 170.0	100.1 - 130.8
Subject 2	106.2 - 164.3	106.4 - 167.2
Subject 3	116.1 - 199.2	115.5 - 188.6
Subject 4	100.2 - 159.2	102.6 - 163.5
Subject 5	100.9 - 196.2	100.0 - 188.5
Subject 6	100.2 - 169.0	100.1 - 157.9
Subject 7	102.3 - 151.6	103.9 - 130.8
Subject 8	102.1 - 206.1	103.9 - 215.5
Subject 9	101.8 - 211.0	103.9 - 211.6
Subject 10	101.5 - 207.0	100.2 - 215.7
Subject 11	107.8 - 224.6.	107.7 - 223.2
Subject 12	101.6 - 184.2	98.84 - 178.7
Subject 13	102.0 - 180.0	103.9 - 180.9
Subject 14	97.81 - 189.0	98.76 - 189.9



(a) (b)

(c)

Figure 4: Testing scenario 1: a) Fatigue time spectral map, b) the same information by a line graph, and c) the ground truth data measured obtained by the dynamometer for one of the test subjects. The blue region is the resting time and the red region shows the fatigue due to exercise.

3.2 Testing scenario 2 (submaximal muscles activity)

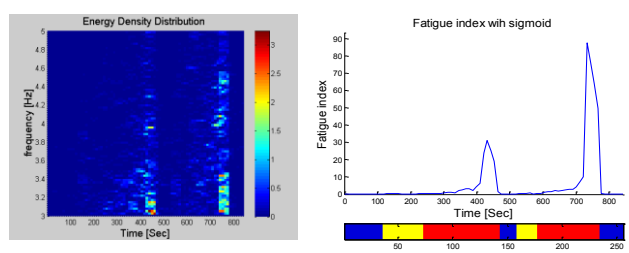
The purpose of this test is to examine the proposed approach for another type of isometric exercise, the submaximal muscles activity. In this type of activity, the muscles in contrary to using the dynamometer are not required to exert the maximum force, but they get tired by continuing an exercise. We implemented this scenario by holding a dumbbell.

Six test subjects participating in this testing scenario were asked to look at the webcam for a while without any motion or expression. They were then asked to left a 5KG dumbbell slowly without any fast motion or reaction on their face, and hold the dumbbell as long as possible such that they feel a continuous pain on their shoulders (fatigue), then they rest for around one or two minutes (depending on their tiredness). Finally, they were asked to repeat the lifting weight again, similar to the first time. Table 2 shows the fatigue duration for each participant. Figures 5(a) and 5(b) show the output of the proposed system by the time spectral map and the line graph for one of the test subjects.

Similar to Figure 4(b) it can be seen in Figure 5(b) that there is a clear difference between the resting and the fatigue regions. However, it can be seen that when the exercise starts in the testing scenario 1, the fatigue index increases sharply, while it rises smoothly in the testing scenario 2. The difference is due to the different types of exercises in the two scenarios. In the testing scenario 1, we used maximal muscle activity while in the testing scenario 2 we used submaximal activity, which does not require maximum power to lift the dumbbell at the beginning.

Table 2: Fatigue duration for lifting the dumbbell at the first and the second attempts.

Subjects	First Attempt			Second Attempt		
	Lift up (Sec.)	Lift down (Sec.)	Fatigue Duration(Sec.)	Lift up (Sec.)	Lift Down (Sec.)	Fatigue Duration(Sec.)
Subject 1	120	220	200.4 - 223.5	300	480	339.1 - 493.1
Subject 2	130	310	167.5 - 293.1	430	550	418.8 - 544.4
Subject 3	125	380	146.9 - 384.2	496	742	508.5 - 757.1
Subject 4	123	379	172.4 - 381.2	476	618	535.4 - 599.0
Subject 5	125	280	230.1 - 283.8	392	502	452.5 - 506.2
Subject 6	128	420	226.5 - 431.4	520	720	539.2 - 733.4



(a) (b)

Figure 5: Testing scenario 2: a) Fatigue time spectral map, b) the same information by a line graph for test subject 5. Blue, yellow and red regions indicate resting time, exercise without fatigue and exercise with fatigue, respectively.

4. CONCLUSION

Muscle fatigue is nowadays measured by some sensors that need to be in direct contact with muscles. The proposed system in this paper consists in a novel contactless muscle fatigue measurement algorithm by detecting and tracking facial features. The proposed system has been tested on 20 test subjects in two different testing scenarios. Comparing the results of the proposed system against the results obtained by contact-based sensors shows that our system finds the fatigue indexes (thresholds between resting and fatigue areas) properly.

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