A Rule Based Framework for Smart Training Using sEMG Signal

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Abstract The correctness of the training during sport and fitness activities involving repetitive movements is often related to the capability of maintaining the required cadence and muscular force. Muscle fatigue may induce a failure in maintaining the needed force, and can be detected by a shift towards lower frequencies in the surface electromyography (sEMG) signal. The exercise repetition frequency and the evaluation of muscular fatigue can be simultaneously obtained by using just the sEMG signal through the application of a two-component AM-FM model based on the Hilbert transform. These two features can be used as inputs of an intelligent decision making system based on fuzzy rules for optimizing the training strategy. As an application example this system was set up using signals recorded with a wireless electromyograph applied to several healthy subjects performing dumbbell biceps curls.

Keywords Surface electromyography (sEMG) · AM-FM decomposition · Muscle fatigue · Exercise cadence · Training · Fuzzy logic · Intelligent system

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1 Introduction

Often sportive or training activities require the execution of repetitive movements. For some activities, such as cycling, running, the estimation of muscle metabolism is based on heart rate, oxygen uptake, lactate production, ventilatory threshold and other variables commonly used in sports medicine [15] requiring special instrumentation such as the cycloergometer. Additionally, recording forces produced by muscles during many physical performances is equally unpractical, often requiring use of special force or torque sensors, which can be bulky, expensive, and not user friendly.

The analysis of surface electromyography (sEMG) signals offers a simple alternative method for quantifying [9] and classifying [24] the muscular activity, and can be a practical tool when exercising on strength training machines or lifting freeweights, to set up ad-hoc training sessions, maximize efficiency, and even preventing injuries [16].

The spectral parameters derived from the EMG signal, such as mean frequency or median frequency, can be used to evaluate muscular fatigue [13, 21, 22, 25]. In fact, during a sustained isometric contraction, there is an increase in the amplitude of the low frequency band and a relative decrease in the higher frequencies, which is called EMG spectrum compression [27].

However, for dynamic or cyclic movements, or for contraction levels higher than 50 % of maximum voluntary contraction, the EMG is a non-stationary signal, thus the physical meaning of the overall spectrum is reduced since amplitude and frequency change over time. To deal with this variability, more sophisticated signal analysis techniques have been proposed [2, 5, 6, 17, 18, 26].

Sinusoidal AM-FM models are representations of signals that can be considered as resulting from simultaneous amplitude modulation and frequency modulation, where the carriers, amplitude envelopes, and instantaneous frequencies (IFs) need to be estimated [10–12]. Recent works have proposed different methodologies based on AM-FM models for evaluating fatigue from EMG signal in repetitive movements [1, 4, 14, 19].

The mean frequency of the amplitude spectrum (MFA) of the EMG signal, considered as a function of time, is directly related to the dynamics of the movement performed and to the fatigue of the involved muscles. If the movement is cyclic, MFA will display the same cyclic pattern, but its average will tend to decrease as the muscle becomes fatigued, due to the reduced conduction velocity of muscle fibers that cause a shift of the spectrum towards lower frequencies. These two effects have been simultaneously modeled by a multicomponent (two-component) AM-FM model [3].

More in detail we applied to the MFA of the EMG signal an AM-FM technique based on the Hilbert transform that is able to simultaneously extract features that are estimations of the cadence and of the resulting muscle fatigue. These features represent a simple and near real-time "summary" of the exercise and can be used by a fuzzy-rule-based decision making system to direct and try to maximize the effectiveness of the training.

Fuzzy-based decision making systems [20] are particular suitable for this kind of application as they can easily embed the vast amount of knowledge on training that can be collected from experts in the field. They are also well suited to *ad hoc* hardware and software implementation of their fuzzy membership functions (MFs), as reported in [7, 8, 23], and the parameters of their MFs can be estimated by using data obtained from previous exercises.

2 Exercise Evaluation

In order to evaluate the exercise execution and its potential effects on the training activity, we record an sEMG signal from the involved muscle and extract some fundamentals parameters according to the algorithm presented in [3] and briefly summarized in the following.

A flow-chart of the whole system is depicted in Fig. 1. First, a feature extractor simultaneously estimates both the cadence at which the exercise was performed and the resulting muscle fatigue. This data is then fed into a fuzzy engine, which ultimately gives suggestions as to how to proceed in the training, and whose rules are determined beforehand in accordance with the training objectives.

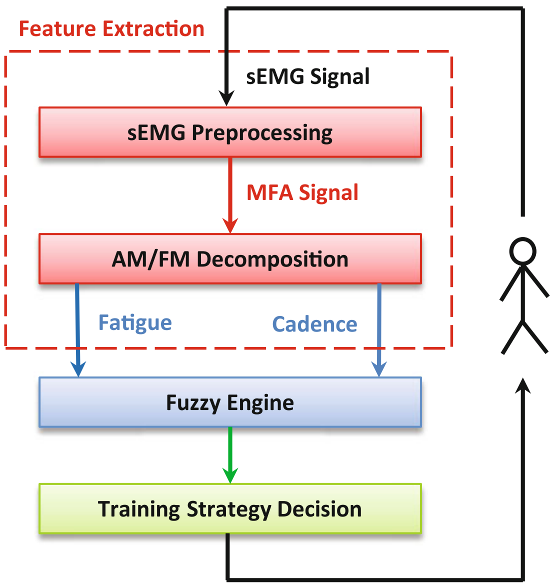

Fig. 1 Flowchart of the system

2.1 *sEMG Feature Extraction*

The recorded sEMG signal is first conditioned by passing it through a high-pass filter to remove some of the acquisition artifacts (e.g., due to cable movement), then the background noise during rest periods is cancelled. Let $y(t)$ be this cleaned signal. We compute the MFA trajectory from its sliding fast Fourier transform $Y(t, \omega)$, as

$$x(t) = \frac{1}{2\pi} \frac{\int_0^{f_H} \omega \, |Y(t, \omega)| \, d\omega}{\int_0^{f_H} |Y(t, \omega)| \, d\omega} \quad (1)$$

where f_H is the bandwidth of the electromyograph used to record the signals.

An example of such an MFA trajectory is shown in Fig. 2, together with its corresponding EMG signal. Its shape suggests that it can be well approximated by a simple two-component AM-FM model

$$x(t) \simeq \sum_{i=1}^{2} \hat{a}_i(t) \cos\left(\hat{\varphi}_i + \int_0^t \hat{\omega}_i(\tau) \, d\tau\right) \quad (2)$$

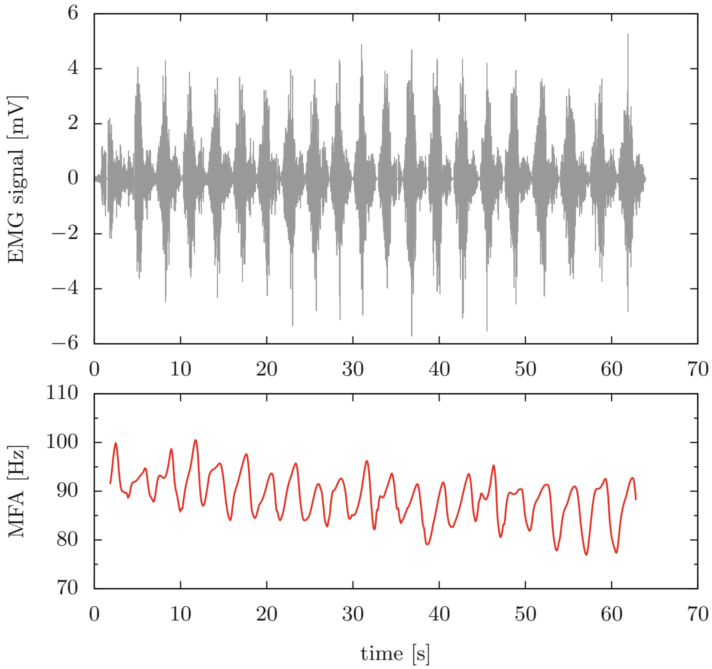

Fig. 2 EMG signal recorded from the *biceps brachii* muscle during a biceps curl exercise with a 3 kg dumbbell (top), and corresponding MFA trajectory (bottom)

where $\hat{a}_i(t)$, $\hat{\varphi}_i$, and $\hat{\omega}_i(t)$ are the estimated component's amplitude, initial phase, and frequency, respectively. The first component models the slowly time-varying average frequency decreasing trend due to fatigue, and the second component models the oscillations in frequency due to the various phases of performing the exercise, thus allowing the cadence to be extracted.

The trend of $x(t)$ is thus captured by the amplitude of the first component $\hat{a}_1(t)$ alone, with $\hat{\omega}_1(t) \simeq 0$ since the fatigue status is generally monotonic and not cyclic during a single exercise. On the other hand, the amplitude of the second component has little meaning (it's the difference between the "peak" and the "mean" MFA during one cycle of the movement), but its frequency $\hat{\omega}_2(t)$ corresponds to the cadence at which the exercise was performed. Figure 3 reports an example of these curves extracted by the algorithm in [3] from the signal of Fig. 2. The amplitude of the first component $\hat{a}_1(t)$ fits with the decreasing trend of $x(t)$, while $\hat{f}_2(t) = 2\pi\,\hat{\omega}_2(t)$ fits the (possibly varying) pace of the exercise.

A well-known fatigue index is the relative slope of the linear regression of $\hat{a}_1(t)$, that is, β/α if $\hat{a}_1(t) \approx \alpha + \beta\,t$. This value is reported, together with the mean cadence, in Table 1, which shows results obtained from 5 healthy subjects performing biceps curl exercises with different weights ranging from 2 kg to 7 kg, selected according to the level of fitness of each individual.

3 Fuzzy Engine for Training Strategy Decision

Once an exercise is performed, we have the two parameters called "fatigue" and "cadence" extracted as previously described. These are used as inputs to a fuzzy engine whose rules come from already available training experience.

An example is given below. We consider the problem of selecting the proper weight for training the *biceps brachii* muscles. The data reported in Table 1 can be used to help derive the shape of a few membership functions. For instance, the fatigue has been classified as "low", "medium", or "high" according to the weight selected by the subject. We assume that a 2 kg dumbbell produced a "low" fatigue status, and so on. The data from the 7 kg exercise was not used as there were not enough points. For each class we discarded the lowest and highest measurement and considered the remaining range of values as 100 % belonging to that class. Membership functions (MFs) are then tapered between these selected ranges, as shown in Fig. 4. The expected output of the system is a hint on the weight to use next, expressed as a percentage of increment, whose MFs are also shown in the same figure.

The set of rules used by the system are reported in Table 2, and the resulting input-output function in Fig. 5. For the inference algorithm, we used the mix/max functions for logic operations, product/sum functions for implication and aggregation, and centroid-based defuzzyfication.

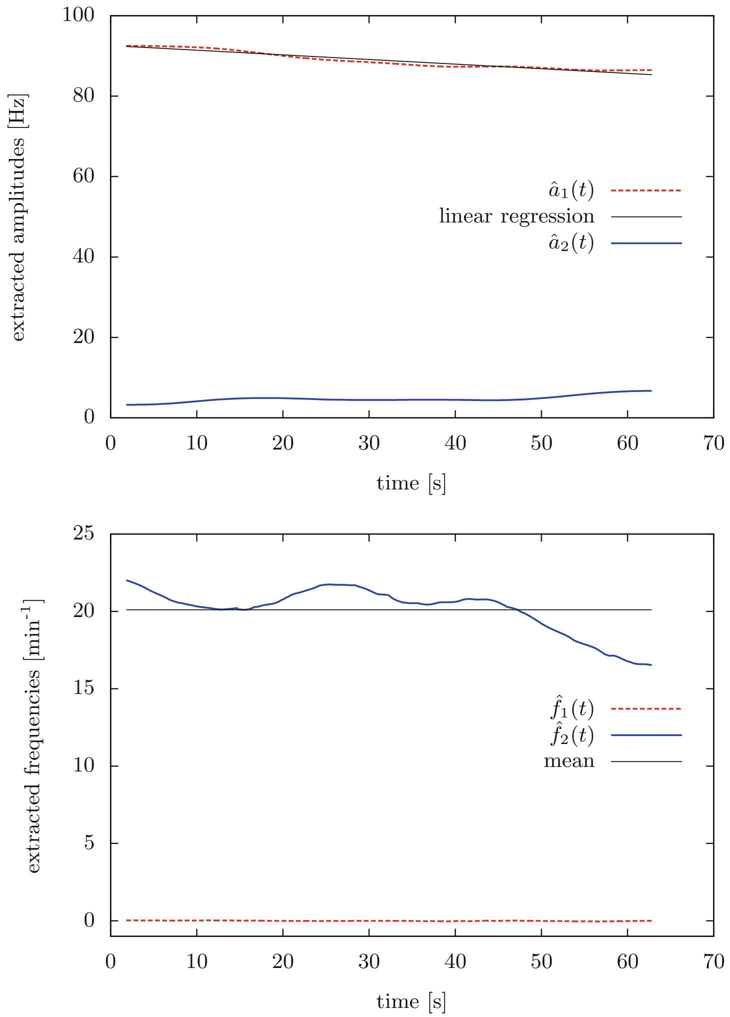

Fig. 3 Demodulated amplitudes and frequencies from the MFA signal of Fig. 2. The linear regression of $\hat{a}_1(t)$ and the mean of $\hat{f}_2(t)$ are also shown as they are used to obtain a compact representation of fatigue and cadence for the overall exercise

To validate the effectiveness of the set of rules previously enumerated, the outcome of the fuzzy engine was computed for each of the input corresponding to the data reported in Table 1. Results are shown in Table 3. The obtained results seems to be in good accordance to the level of fitness declared by the subjects that performed the exercise.

Table 1 Fatigue test performed on 5 healthy subjects: estimated rate of MFA variation and mean cadence, [%/ min] @ [reps/ min]. Data from [3]

Subject	Weight			
	2 kg	3 kg	5 kg	7 kg
subject 1	−7.9 @ 17.7	−4.2 @ 20.5	−12.4 @ 21.4	
subject 2	−0.6 @ 23.5	−9.8 @ 21.7	−30.3 @ 18.6	
subject 3	−1.2 @ 20.9	−7.5 @ 20.1	−19.1 @ 18.3	
subject 4		−7.4 @ 23.4	−16.8 @ 24.5	−23.7 @ 20.4
subject 5		−12.0 @ 22.4	−14.3 @ 24.9	−34.3 @ 22.6

Table 2 Inference rules used to select the next weight to use. The "=" symbol means keep the current weight, "−" decrease the weight, "+" increase the weight, "++" increase much the weight

		cadence		
		slow	right	fast
fatigue	high	−	=	=
	med	=	+	+
	low	=	+	++

4 Conclusion

In this paper an efficient framework to aid in the selection of a training strategy to improve muscular strength has been presented. The framework uses a lightweight wireless electromyograph applied on the involved muscles, and from the sEMG signal thus recorded both the muscular fatigue and the repetition frequency during the accomplishment of cyclic movements is estimated, by means of a two-component AM-FM decomposition based on the Hilbert transform.

These two features have been used as inputs of a fuzzy rule-based pattern recognition system whose outputs are the guidelines needed for optimizing and customizing individual training sessions. As an application example, some experimental data extracted from dumbbell biceps curls have been used to set-up the fuzzy system and obtain the input-output relationship for this kind of exercise employing inference rules written by exploiting knowledge on training techniques.

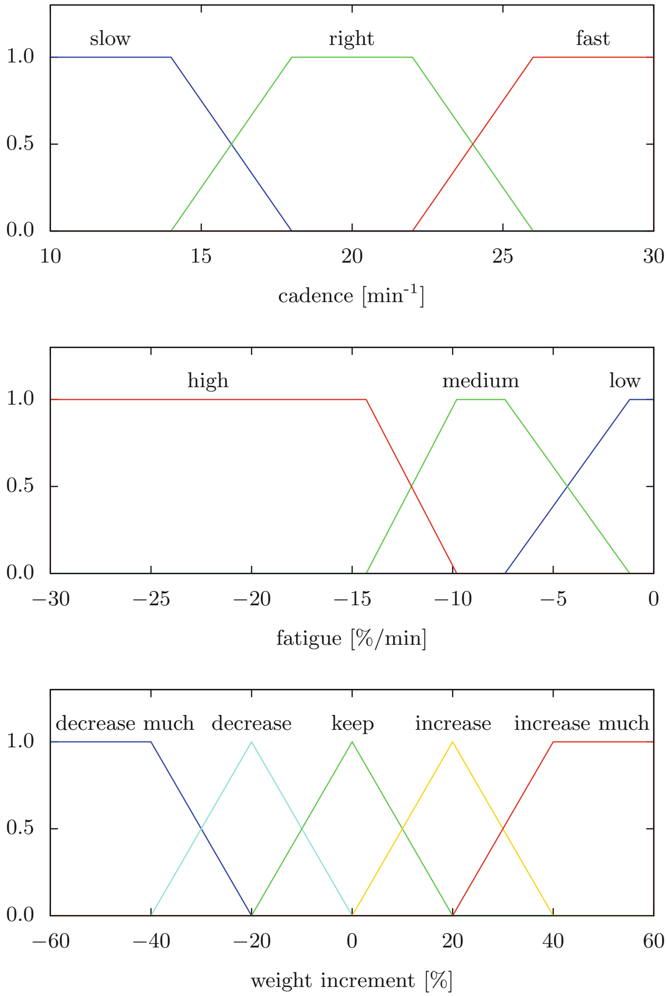

Fig. 4 Membership functions of the inputs and output of our fuzzy system

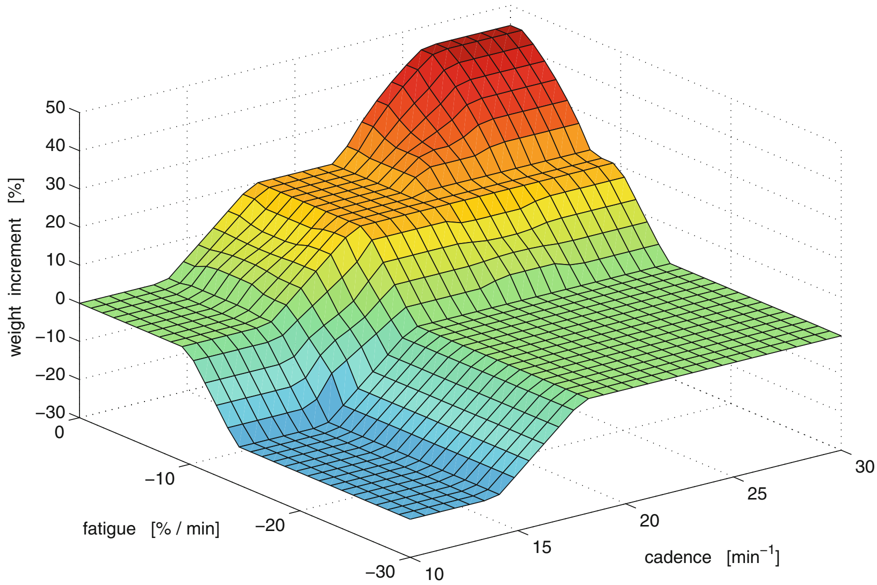

Fig. 5 Input-output relation resulting from the fuzzy rules reported in Table 2

Table 3 Results of the application of the fuzzy engine on the data of Table 1: suggested increase of the weight [%]

Subject	Weight			
	2 kg	3 kg	5 kg	7 kg
subject 1	+18.5	+20.0	+8.4	
subject 2	+31.9	+20.0	0.0	
subject 3	+20.0	+20.0	0.0	
subject 4		+20.0	0.0	0.0
subject 5		+10.2	0.0	0.0

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