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Classification of muscle activity based on effort level during constant pace running

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ABSTRACT

During running, psychologic and physiologic changes are manifested in the perception of effort, muscle properties and movement strategies. The latter two aspects are expressed as changes in electromyographic (EMG) activity. This paper tests the hypothesis that the EMG signals change in a systematic way during a run and that these changes are related to the effort level of the runner. Fifteen female recreational runners performed 1-h treadmill runs at a constant speed (95% of speed at ventilatory threshold). EMG signals were recorded from four muscles (tibialis anterior, gastrocnemius medialis, vastus lateralis, and semitendinosus). The wavelet transformed EMG data were used to discriminate between different effort phases of running using a support vector machine (SVM) approach. The effect of the penalty parameter, *C*, and cross validation folds, *n*, used were evaluated and found to have little influence on the outcome. Recognition rates of >80% were achieved for all *C* and *n* values across all muscles. Average recognition rates were: TA – 89.2, GM – 88.3%, VL – 84.6% and ST – 94.0%. These results suggest that selected lower extremity EMG signals using wavelet-based methods contained highly systematic differences that could be used by the SVM to discriminate between the low- and high-effort stages of prolonged running.

1. Introduction

During the course of a prolonged run, both central control and peripheral factors may change and influence psychologic and physical characteristics of the locomotor system (Kyröläinen et al., 2000; Martin et al., 2010). For example, the perception of effort, has been shown to increase linearly over the course of a constant load exercise (Noakes, 2004). Over the course of a run, altered muscle properties (Brody et al., 1991) and/or movement strategies (Williams et al., 1991) can be expressed as changes in electromyographic (EMG) activity. In particular, muscle fatigue has been shown to manifest itself as a decrease in the mean frequency of the EMG signal resulting from a reduction in the conduction velocity of the action potential along the muscle fibers (Brody et al., 1991; Knaflitz and Bonato, 1999). In addition, wavelet transformed EMG signals (von Tscharner, 2000) show precisely timed muscular events during a movement (von Tscharner and Goepfert, 2006; Stirling and von Tscharner, 2010). It is currently unknown if these fine muscle event structures contain information about the fatigue state of the muscle. It is possible that subtle aspects of the intensity, timing and frequency of the EMG signal change over the course of muscle activity.

The current development in new analysis tools provides the possibility to address this question. In particular, the ability to represent wavelet transformed EMG signals as vectors in a vector space (von Tscharner, 2002) has allowed vector-based analysis methods to be applied. Methods that have previously been applied in conjunction with wavelet transformed EMG include principal component analysis (von Tscharner, 2002; von Tscharner and Goepfert, 2003) and novel classification methods (von Tscharner, 2009). These approaches have resulted in the identification of differences in EMG signals based on shoe conditions (von Tscharner et al., 2003), gender (von Tscharner and Goepfert, 2003), disease state (von Tscharner and Valderrabano, 2010), and fatigue (von Tscharner, 2002).

A support vector machine (SVM) classifier is another powerful vector-based method (Scholkopf and Smola, 2001; Shawe-Taylor and Cristianini, 2004). The SVM has been applied widely to applications ranging from bioinformatics to computer vision, including the detection and recognition of faces, hand-written characters as well as DNA-sequences (Byun and Lee, 2002). The SVM has been applied to biomechanic data for the classification of gait based on age (Begg and Kamruzzaman, 2005), injury (Lai et al., 2009), pregnancy (Gilleard et al., 2008), and pathology (Guler and Kocer, 2005). Applications of the SVM to EMG have been used for motion classification (Yan et al., 2008) as well as the classification between strength and endurance-trained athletes (Huber et al., 2010).

We hypothesized that the amplitude, timing and frequency of fine muscle event structures within EMG signals change in a

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systematic way during a prolonged run and that these changes are related to the effort stage of the runner. If so, one should be able to use a time–frequency decomposition of the EMG to discriminate between signals measured during the low effort and higher effort stages of a constant-pace, moderate intensity run. In this study, measurements of perceived exertion (Borg, 1982) were combined with a wavelet based time–frequency analysis (von Tscharner, 2000) and support vector machine classification (Scholkopf and Smola, 2001) to discriminate between high and low effort stages of running.

2. Methods

Fifteen female recreational runners (age 30.8 ± 7.6 years, mass 60.8 ± 5.9 kg) participated in this study. The protocol was approved by the Conjoint Heath Research Ethics Board at the University of Calgary and subjects gave their informed consent.

2.1. Measurement protocol

All participants performed a 1-h endurance run at approximately 95% of their speed at ventilatory threshold, while EMG signals were recorded from the tibialis antrior (TA), gastrocnemius medialis (GM), vastus lateralis (VL) and semitendinosus (ST) muscles. Speed at ventilatory threshold (sVT) was determined by monitoring respiratory gas exchange (Cosmed K4b2, Rome Italy) during an incremental running test on a motorized treadmill (Quinton Instrument Co., Seattle, WA, USA). Belt speed was increased by 0.13 m/s every 2 min until the subjects reached sVT (Wasserman et al., 1973; Skinner and McLellan, 1980).

In preparation for the EMG measurements, the skin was lightly abraded, cleaned with alcohol and bipolar Ag/AgCl surface electrodes (Noratrode dual electrodes, Noraxon USA Inc., Scottsdale, AZ, US) were placed on the belly of each muscle in alignment with the direction of the muscle fibers (according to standards provided by Seniam.org). This placement insured that the electrodes were not located over the innervation zone of the muscle. All electrodes were placed by a single experimenter to insure consistency thorough the study. Electrodes and amplifiers were secured to the skin using medical tape (Cover-Roll stretch, BSN medical GnbH, Hamburg, Germany) to minimize movement artifact and to prevent the electrodes from losing surface contact due to sweating. Signals were amplified and bandpass filtered (1000×, 10–500 Hz, Biovision, Wehrheim Germany) before being recorded at 2400 samples/s.

Thirty second records were taken at 2 min intervals throughout the run. Heel strike was detected using an accelerometer attached externally to the heel of the right running shoe and recorded simultaneously using an additional channel on the same analog to digital data acquisition system as the EMG signal. In addition, every 6 min subjects were asked to rate their perceived exertion (RPE) using a 15 point Borg scale.

2.2. Data analysis

All occurrences of heel strike were determined during each included 30 s data record by detecting the onset of the sharp deceleration associated with floor contact. A ±300 ms window around heel strike, which included all pre- and post-heelstrike muscle activation associated with the step, was used for the analysis.

2.2.1. Time–frequency analysis using wavelets

A time–frequency analysis of the EMG data was performed using a non-linear wavelet transform (von Tscharner, 2000). The signal during each 600 ms data clip was downsampled by a factor of 4, the wavelet transform was computed, and the average transform for all steps taken in the 30 s record was determined. This resulted in an average EMG intensity pattern for each record where time (362 samples) and frequency (center frequencies of the 13 wavelet filters: 7, 19, 38, 62, 92, 128, 170, 218, 271, 331, 395, 466 and 542 Hz) are indicated on the abscissa and ordinate, respectively, and the grayscale represents the power of the EMG signal (refer to Fig. 1 for an example).

All average patterns, one per 30 s data record, were visually inspected for noise (e.g., movement artifact) and only clean signals were included for further analysis. The values of the pixels in each average intensity pattern were arranged into single row vectors, $\boldsymbol{x}_i$ (each having 4706 elements).

2.2.2. Classification using support vector machine

The SVM is a learning algorithm that operates on the principle of the maximization of the margin between the data and a linear classification boundary (hyperplane) and the minimization of the training error i.e., as many training points as possible should be classified correctly. The penalty parameter $C > 0$ determines the tradeoff between margin maximization and training error minimization. If a high C is chosen, wrongly classified examples lead to a high penalty and forces the classifier to select a solution with a smaller margin (Herbrich, 2001). A lower C allows for more training errors while still a unique solution with maximum margin is found.

To train the SVM classifier, a training data set was provided from which the classifier inferred a decision rule. Each average pattern, $\boldsymbol{x}_i$, was assigned a label, y_i, based on the rate of perceived exertion reported by the subject at the time at which the corresponding EMG record was taken. Patterns corresponding to Borg scores of 12 or less were labeled as low-effort (−1) and those corresponding to Borg scores of 15 or more were labeled as high effort (1). Since EMG data were collected every 2 min and RPE was only reported every 6 min, each RPE record was used to label the previous, current, and following EMG record with an appropriate effort condition. All average patterns, $\boldsymbol{x}_i$, that did not fall within a class (e.g., corresponded to a Borg score of 13 or 14) were excluded from the data set.

A complete training set comprised of a matrix, $\boldsymbol{X}$, with rows containing each of the average patterns, $\boldsymbol{x}_i$, that were assigned to a class, and a column vector, $\boldsymbol{y}$, with elements containing the labels corresponding to each pattern in $\boldsymbol{X}$. The $\boldsymbol{X}$ and $\boldsymbol{y}$ matrices were used to train the SVM classifier. The SVM of the software package libSVM (Chang and Lin, 2010) was used to train the classifier. The classifier is fully defined by the two variables $\boldsymbol{D}$ and b, which are

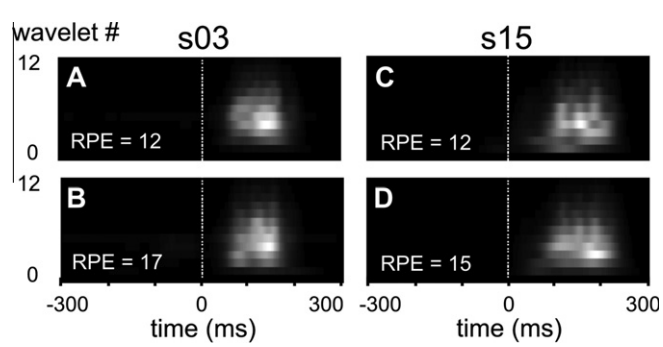

Fig. 1. Example of average gastrocnemius medialis intensity patterns from 2 subjects (columns s03 and s15). Patterns in the top row (A, C) correspond to low effort running (RPE ⩽ 12) and patterns in the bottom row (B, D) correspond to high effort running (RPE ⩾ 15). Black indicates areas of no signal intensity and white indicates the area of greatest signal intensity.

learned from the training set. The vector $\boldsymbol{D}$ is the normal vector of the separating hyperplane and b is the bias (the distance of this hyperplane from the origin). The separating hyperplane divides the data from the two classes such that data on one side corresponds to the high-effort stage and data on the other corresponds to the low-effort stage. A linear function $S(\boldsymbol{x})$ was used to assign an average pattern, $\boldsymbol{x}_i$, to one of the two classes.

$$S(\boldsymbol{x_i}) = sgn(\langle \boldsymbol{D}, \boldsymbol{x_i} \rangle + \boldsymbol{b}) \quad (1)$$

The term $\langle \boldsymbol{D}, \boldsymbol{x_i} \rangle$ denotes the scalar product between $\boldsymbol{D}$ and $\boldsymbol{x}_i$. The discriminant vector, $\boldsymbol{D}$, is normal to the boundary hyperplane, has the same dimensions and resides in the same vector space spanned by the average patterns, and can therefore also be displayed as an intensity pattern. The image of the discriminant provides a visual representation of the features of the training patterns that contributed to the separation of the groups. The solution of the equation $S(\boldsymbol{x}_i)$ for each average intensity pattern, $\boldsymbol{x}_i$, indicated whether the pattern was assigned to the low- or high-effort state. Specific $\boldsymbol{X}$ and $\boldsymbol{y}$ datasets were created for each muscle.

2.2.3. Assessment of classification

The "separability" of the data was computed by using the $\boldsymbol{D}$ to assign all patterns in $\boldsymbol{X}$ to a class and determining the percentage of correctly assigned patterns. An "n-fold" cross validation procedure was then used to determine the general recognition rate for new patterns, ones that were not included in the training set. During an n-fold cross validation test, a fraction $(1/n)$ of the patterns, $\boldsymbol{x}_i$, and their corresponding labels, y_i, were removed from the training set ($\boldsymbol{X}$ and $\boldsymbol{y}$) before using the remaining data to recompute the discriminant, $\boldsymbol{D}$. The removed patterns were then classified using the new $\boldsymbol{D}$, and the relative number of correctly assigned patterns was computed. This was repeated n times, removing a different subset of $\boldsymbol{X}$ each time. The cumulative ratio of correctly assigned patterns is called the "recognition rate". The recognition rate of an n-fold cross validation indicated the probability of correctly assigning an unknown pattern to the correct effort stage.

The SVM contains a penalty parameter $C > 0$ that determines the tradeoff between margin maximization and training error minimization. An optimal value for this parameter had to be found. Seven different C values were used in the SVM algorithm resulting in seven discriminant vectors, $\boldsymbol{D}$, for each muscle. C values corresponding to 10^m (m = 1, 1.5, 2, 2.5, 3, 3.5, 4) were tested. The average separability of the patterns was computed (mean ± std of all seven corresponding C conditions) and plotted. The separability depended only on the parameter C, whereas the cumulative recognition rate depended on both, the C and the n used in the n-fold cross validation. Therefore, an appropriate n was determined. A total of 70 recognition rates were determined per muscle corresponding to the seven different C values (see above), and 10 different n values (2,4,6,8,10,12,14,16,18,20). The influence of each pair, C and n, on the recognition rate was evaluated by determining the average (±std) recognition rate for each n (using all seven C conditions for each n) and the average (±std) recognition rate for each C (using the 10 different n values for each C). The averaged recognition rates were determined and plotted for each muscle. Tables with the full sets of recognitions rates for each C and n value are included in the additional online material. A pair of values for C and n was selected in such a way to optimize the recognition rate for each muscle.

A one sided binomial test was performed to determine the threshold percentage of correctly classified patterns per muscle needed to insure (at the 95% level of confidence) that the patterns were not being randomly assigned to one of the two classes.

3. Results

During the 15 1-h running sessions the average maximum aerobic speed of the subjects was 3.2 ± 0.4 m/s. The subjects ran at an average speed of 3.0 ± 0.3 m/s, corresponding to 94.6 ± 2.1% of their sVT. On average the subjects' Borg scores were 10.9 ± 2.0 at the beginning and 15.4 ± 2.4 at the end of the run. One subject started their run with above the low-effort level, and five of the 16 subjects failed to reach the high-effort stage during their run. The average Borg score corresponding to the low effort stage (RPE $\leqslant$ 12) was 11.2 ± 1.1, whereas the average Borg score corresponding to the high effort stage (RPE $\geqslant$ 15) was 16.2 ± 1.1.

A total of 905 average patterns were included in this study. Table 1 indicates the number of patterns used as input to the SVM for each muscle and the number initially assigned to each of the effort stages. The average number of patterns per subject was 12.0 ± 10.1 and 9.7 ± 8.9 for the low- and high- effort stages, respectively. Of the included data, one subject had only high-effort data and 5 subjects had only low-effort data.

The average patterns computed from the EMG signals recorded during different effort stages of the runs were visually not very different. A visual classification was therefore not possible. Examples of patterns from the GM muscle of two subjects are provided in Fig. 1.

Examples of the patterns of $\boldsymbol{D}$ for GM, and VL muscles computed using 2 different C values are shown in Fig. 2. Black and white areas indicated regions where the pattern was found to differ between the low and high effort classes through a decrease or increase in the signal, respectively. Regions in gray represented aspects of the signal that did not discriminate between classes. All muscles showed a similar fine structure to the $\boldsymbol{D}$ vectors. Small differences in $\boldsymbol{D}$ occur with the use of various C values in the SVM algorithm.

An analysis of the effect of C and n on the recognition rates showed that their selection was not sensitive. In general, C values of 1000–10,000 resulted in similar recognition rates, whereas only lower C values resulted in poorer classification (Fig. 3, black circles). An average separability of the patterns of more than 90% was found for different C values (Fig. 3, gray squares). In general, the recognition rate tended to level off for n-fold cross-validations with $n > 4$ (Fig. 3, open circles). The lowest cumulative recognition rate for each muscle always occurred when $n = 2$. The average cumulative recognition rate was largest for the ST (94.0%) muscle followed in decreasing order by the TA, GM and VL muscles (Table 1). The maximum recognition rates achieved for each muscle were: ST-94.4%, TA-93.3%, GM-91.4%, and VL-89.9%. The corresponding C and n values used to achieve these values are included in Table 1. The statistical hypothesis of random assignments to the effort stages was falsified by the fact that the recognition rates of all muscles were higher than the threshold percentage of

Table 1
Summary of patterns included in the analysis, and number of patterns per effort stage. Also listed are the threshold recognition rate required to reject the random assignment of patterns by the SVM, the average recognition rate achieved, the maximum recognition rate achieved and the C and n values corresponding to the maximum result.

Muscle	TA	GM	VL	ST
Total patterns	225	266	248	166
Low-effort	126	154	148	110
High-effort	99	112	100	56
Threshold%	55.6	54.9	55.2	56.6
Avg. recognition rate	89.2	88.3	84.6	94.0
Max. recognition rate	93.3	91.4	89.9	94.4
C	100	316	10,000	10,000
n	4	4	12	14

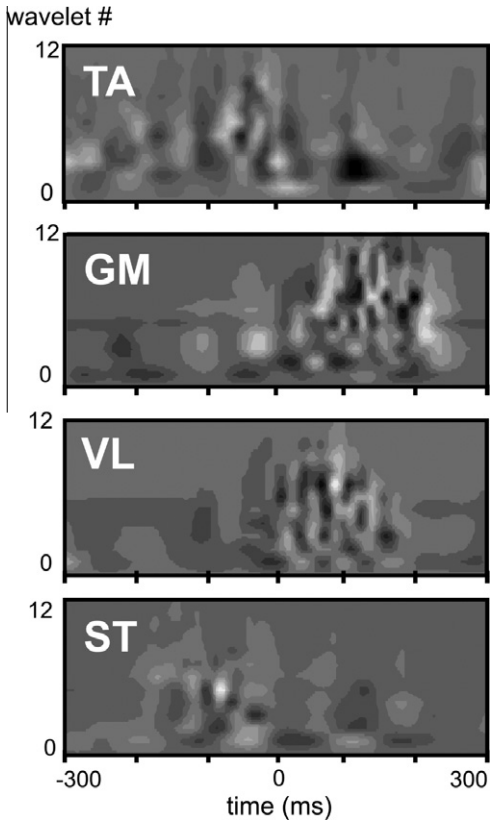

Fig. 2. Patterns representing the discriminant vector, ***D***, providing the highest recognition rate between the low and high effort stages for each muscle. The *C* values used were: TA-100, GM-316, VL-10,000 and ST-10,000. White indicates areas in the pattern where the average EMG patterns showed more intensity in the high-effort stage, and black indicates areas where there was more intensity in the low-effort state.

54.1 ± 0.4% (Table 1) obtained for any combination of *C* and *n* values.

4. Discussion

The average patterns of the EMG signals extracted using wavelet-based methods contained highly systematic differences between the low- and high-effort stages of prolonged running. Discriminant vectors existed for each of the four muscles tested and lead to a successful classification of EMG data collected with recognition rates greater than 80%. This supports the use of a combination of the wavelet transform and a SVM classification algorithm as a powerful tool for separating EMG data recorded during different effort stages.

When using the SVM one must consider parameters that may influence the recognition rates achieved. These parameters include the penalty parameter, *C*, indicating the tradeoff between margin maximization and training error minimization, and the number of folds, *n*, used in the cross-validation procedure. The results from this study suggest that there is not a high sensitivity of the recognition rates to the selection of these parameters. This may be the reason that very little advice was found in the literature about the selection of these values. The use of *C* values between 1000 and 10,000 results in a recognition rate that is generally optimal. Cross-validation procedures in which less than 25% of the data is removed at a time ($n > 4$) also result in stable recognition rates. These parameter ranges can be used in future studies where the SVM is applied without having to repeat the iterative selection methods used here.

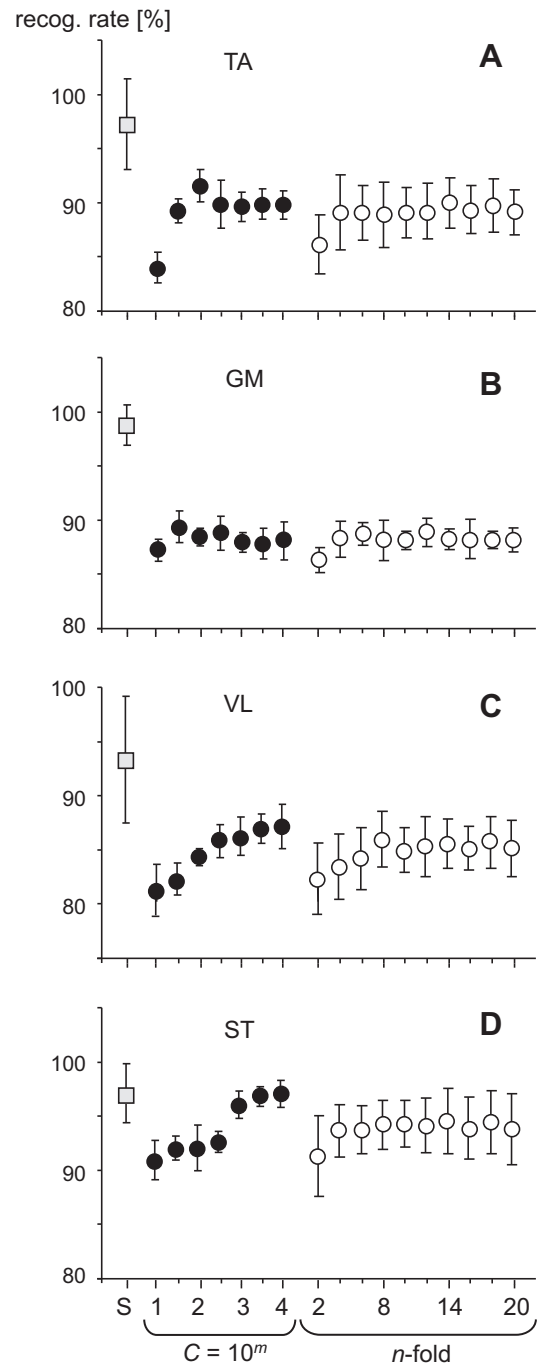

Fig. 3. Separability (gray square), and recognition rates computed for different *C* (black circles) and *n*-fold (open circles) values. Each plot represents the results from a different muscle (A-TA, B-GM, C-VL, D-ST).

Methods such as principal component analysis and spherical classification have been previously used to separate EMG wavelet patterns belonging to different gender (von Tscharner and Goepfert, 2003), footwear (von Tscharner, 2009), and pathological (von Tscharner and Valderrabano, 2010) conditions. In those cases it was often difficult to visually distinguish between EMG wavelet patterns from the different classes despite the fact that many of these conditions were associated with stereotypical changes in biomechanics. For example, barefoot running is associated with a more midfoot strike relative to shod runners and was reflected in an earlier and higher frequency post-heelstrike activation of TA (von Tscharner et al., 2003). In this study, the distinguishing

features between average patterns corresponding to the low- and high-effort stages were expected to be more subtle and were likely to reflect aspects of fatigue. The role of fatigue is supported by the fact that during constant load exercise the perceived exertion of the athlete increases linearly until exhaustion is reached and the exercise is terminated (Noakes, 2004). This corresponds to the fact that subjects tended to progress from low- to high-effort over the course of the 1-h run protocol used in this study. Therefore, changes in muscle fiber properties and motor control strategies corresponding to fatigue must be considered as sources for the shifts in EMG frequency and timing seen in the patterns of the discriminating ***D*** vectors.

If fatigue is the key aspect influencing the EMG patterns, the ***D*** vector would be expected to reflect a shift of the EMG spectrum to lower frequencies for the high-effort stage of the run. However, this was not visible in the patterns representing the discriminant vectors shown in Fig. 2. Instead, the patterns were characterized by fine structures within the region of main muscle activity. These fine structures seem to reflect information about the neuromuscular control strategy employed. One possibility, among others, would be that the patterns reflect the feature known as the Piper rhythms in the EMG activity (Piper, 1907; Brown, 2000). Rhythmicity has recently been demonstrated by our group to be modified with muscle fatigue during isometric contractions (von Tscharner et al., 2010). In addition, we have shown that the Piper rhythm exists in the bursts of muscle activity during running, indicating a central component of the neuromuscular activation (Stirling and von Tscharner, 2010). The possible role of the Piper rhythm in discriminating between the phases of a prolonged run will be investigated in further studies.

Limitations of this study include the possibility that the development of additional noise and movement artifact throughout the course of the run contributed to the high classification of the data. A deterioration of the affixation of the electrodes to the skin would influence the EMG signals, particularly during the later high-effort stage of the run. However, these affects are not likely due to the fact that all signals were carefully visually inspected and all those containing signs of noise or movement artifact were removed from the analysis. Also, in this study the maximum Borg score reached during the run varied between subjects because the participants were not asked to run to exhaustion. Thus the patterns during the high-effort stage of the run were not representative of extreme fatigue. Our aim was to first establish the association between EMG patterns and effort stage during an aerobic exercise protocol that is representative of training performed by many athletes before pushing for the extreme.

Apart from the linear SVM, more powerful non-linear SVM can be used for classifying the patterns. Some of the non-linear approaches that were tested in our laboratory resulted in better recognition rates (results were not shown), however, one loses the important information contained in the pattern of the discriminant, ***D***. Thus there is a trade off of between getting a higher recognition rates and knowing the features of the patterns that led to the classification. Once the robustness and understanding of the features leading to the classification is well established one may progress to these more sophisticated methods. For the time being, the application of pattern recognition methods to EMG signals is still a very complex undertaking.

The approach described in this study moves beyond current methods where single variables extracted from EMG signals (e.g., mean frequency) are correlated to fatigue. Using the current method, the full information from the signal is provided as input to the classifier. The result is a discriminant that provides a strong ability to classify EMG signals from different running states. Once an understanding of the features within the discriminant is achieved, a new set of simplified EMG features may lead to a simplified, but equally strong, classification of EMG data.

5. Conclusion

The present study confirmed that the features of the EMG signal change in a systematic way during a prolonged run and that these changes are related to the effort stage of the runner. This was demonstrated by the fact that EMG measured during the low effort and higher effort stages of a moderate intensity run could be discriminated by combining the wavelet based time–frequency analysis and a SVM classification algorithm. With this approach we were able to classify, with a high recognition rate (>80% for all muscles tested) new EMG patterns obtained during 30 s records as belonging to the low- or high-effort stages of the run. The fact that wavelet transformed EMG signals can be classified based on such fine differences such as the effort stages of a runner during a prolonged run opens the door to many future applications in research, clinical and training settings. For example, classification may be simplified to a point where coaches can use the technology to identify changes in their athletes from start to finish of a run.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.jelekin.2011.02.005.

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