LOWER LIMB MUSCLE RECRUITMENT STRATEGIES DIFFER BETWEEN ELITE AND RECREATIONAL ICE HOCKEY PLAYERS

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Understanding the muscle recruitment strategies that have the largest contribution to performance is essential in sports biomechanics. The aims of this study were to characterise principal muscle activation patterns during accelerative hockey skating and to classify skill levels of players based on their principal muscle activation patterns. Key features of lower limb muscle activation strategies during accelerative skating were extracted and used to classify, with 83% success, elite and recreational players' acceleration strides. Classification and functional interpretation of muscle coordination is important to understand the differences in muscle recruitment strategies across skill levels, and to monitor changes that result from training.

KEYWORDS: Principal component analysis, support vector machine, electromyography.

INTRODUCTION: The game of ice hockey is a fast-paced, complex, team sport, which demands quick thinking, fast reactions, and superior athletic skills. Skating ability, in particular, is a key feature of a highly skilled ice hockey player. In fact, ice hockey is characterised by explosive skating patterns, where players who are able to increase their speed (i.e. accelerate) at greater rates than their rivals can gain substantial performance advantages (Upjohn et al., 2008). Athlete performance and task quality is often viewed to result from interactions of biomechanical variables and muscular activation strategies. Therefore, in order to improve skating performance, a biomechanical understanding of the muscle recruitment strategies that have the largest contribution to skating performance is essential.

Classification and functional interpretation of muscle coordination can be obtained through the analysis of human movement, and both are important for understanding the interplay of muscle activities that lead to high level performance. Vector-based pattern recognition methods such as principal component analysis (PCA) and support vector machines (SVM) enable identification of underlying movement features, and subsequent classification of skill levels based upon extracted features. These methods have largely been applied to the classification of gait and running patterns with respect to *age* (Fukuchi et al., 2011) *gender* (Maurer et al., 2012), and comparisons between injured and uninjured limbs (von Tscharner & Valderrabano, 2010); however, these methods have, to the authors' knowledge, never been applied to the classification of skill sets within a sporting context. Identification of muscle recruitment strategies that separate elite from recreational athletes have strong coaching implications, as it would allow for the identification of the strategies that are required to perform important movements at the highest level. Therefore, the purpose of this study was to (a) identify principal muscle activation patterns during accelerative hockey skating and (b) classify skill levels of players based on these principal muscle activation patterns.

METHODS: Nine elite (25.7±3.7 yrs, 86.2±7.8 kg) and nine recreational hockey players (35.7±5.7 yrs, 85.7±13.6 kg) participated in this study. Each group performed 15 repetitions of a 30 m maximum effort forward skating task on an Olympic–standard ice hockey rink. Performance times were measured using timing light gates (Brower Timing Systems, Draper, UT, USA), which enabled the times for the first 10 m of the sprint (i.e. acceleration phase), as well as the full 30m sprint to be recorded.

Muscle activity was measured from the muscle bellies of the right leg for the tibialis anterior (TA), medial gastrocnemius (MG), vastus medialis (VM), vastus lateralis (VL) and gluteus medius (GM) using Ag-AgCl bipolar surface electrodes (Biovision, Wehrheim, Germany). Voltage signals from EMG electrodes were pre-amplified at the source and sampled at 2400 Hz. For each muscle, EMG signals were resolved into time-frequency space using wavelet analysis, which involves a convolution of 13 non-linearly scaled wavelets (centre frequencies ranging from 6.9 Hz to 542 Hz) with the raw signal (von Tscharner, 2000). Wavelet transformed EMG signals were normalised to the mean power of each muscle. EMG electrodes were directly connected to a data acquisition unit (Biovision, Wehrheim, Germany) which was housed inside a backpack that also contained an analog-to-digital converter, and a tablet (Acer Iconia W 510, Acer Inc., Taipei). Data from the analog-to-digital converter was recorded with the tablet and a wireless connection was formed with an external laptop, which allowed for the control of data acquisition and recording.

EMG from the second stride of the forward skating drill, where the skate was in contact with the ice, was extracted and time-normalised according to the ice contact phase (% ice contact). The second stride was selected as it represents the *accelerative* portion of forward skating (Pearsall et al., 2001). Specifically the ice-contact phase was extracted, as this is where force production and muscle activity are greatest. Ice contact was determined by the sudden onset and offset of high vibration amplitudes in the skate chassis accelerometer signal.

For the PCA, wavelet transformed EMG data from all trials of all subjects were used as inputs into a PCA matrix. The input matrix was 27270 by 65 in size, with the rows representing 101 time normalised data points of 15 trials from 18 subjects. The 65 column vectors (i.e. variables) were the power extracted by the wavelets (13 wavelets x 5 muscles) at each time normalised point. The mean of each vector was subtracted from the matrix.

PCA was applied to the above dataset, which involved an orthogonal transformation of the data into a new set of uncorrelated principal component loading vectors. PCA transformation results in a set of eigenvectors which were arranged in descending order according to their explained variance of the original data set. It follows that the first component describes the most relevant aspects with respect to muscle recruitment strategies during skating. In this analysis, the first set of principal components that explained at least 95% of the total variance in the dataset was retained in the model. While this causes some details in the dataset to be discarded, a key advantage of PCA is its data reduction capabilities, where only the data which contributes to the largest variance is analysed.

Principal component (PC) scores for individual subjects were obtained by projecting the original time-series data onto each of the retained principal component vectors. PC scores represent the correlated firing pattern of muscles and were used as inputs to a linear SVM, in order to assess differences between skill sets. PC scores for the elite subjects' trials were stacked on top of those of the recreational subjects. The SVM binomially classified trials by determining the optimal separating hyper-plane which maximised separation between the two groups' data. The leave-one-out cross validation approach yields a *classification rate,* which tells us the percentage of acceleration strides that were classified correctly according to hockey player caliber. Statistical significance of the classification rate was assessed using a binomial test.

RESULTS: In terms of sprint performance, the elite group skated the acceleration phase and the total sprint distance 11.7% and 11.2% faster, respectively, than the recreational group ($p<0.05$).

The multi-muscle intensity pattern of Figure 1a represents averaged muscle activity across all subjects during the ice contact phase of an acceleration stride.

Following the PCA transformation, 22 PC vectors were seen to explain more than 95% of the variance of the original dataset, which contained 65 features. The dominant muscle activation strategy (i.e. PC1) during an ice hockey acceleration stride was the simultaneous activation of the hip abductor muscle (GM), and the two knee extensor muscles, VM and VL (Figure 1b). This was followed by PC2 which showed contributions from MG and VM, and an inverse contribution from VL (Figure 1c). PC1 and PC2 represented 32.0% and 23.7% of the total variance in EMG power, respectively.

Mean PC-score waveforms throughout time were different with respect to caliber, revealing group-dependent differences in muscle recruitment strategies. The hip-knee extensor activity of PC1 was shown to be the dominant strategy in elite hockey skating. On the other hand, recreational players placed greater emphasis on an ankle plantar flexor activity compared to elite, contributing to a greater proportion of variance in PC2. According to the SVM Leave One Out cross validation, 83% of acceleration strides were classified correctly according to skill level ($p<0.05$).

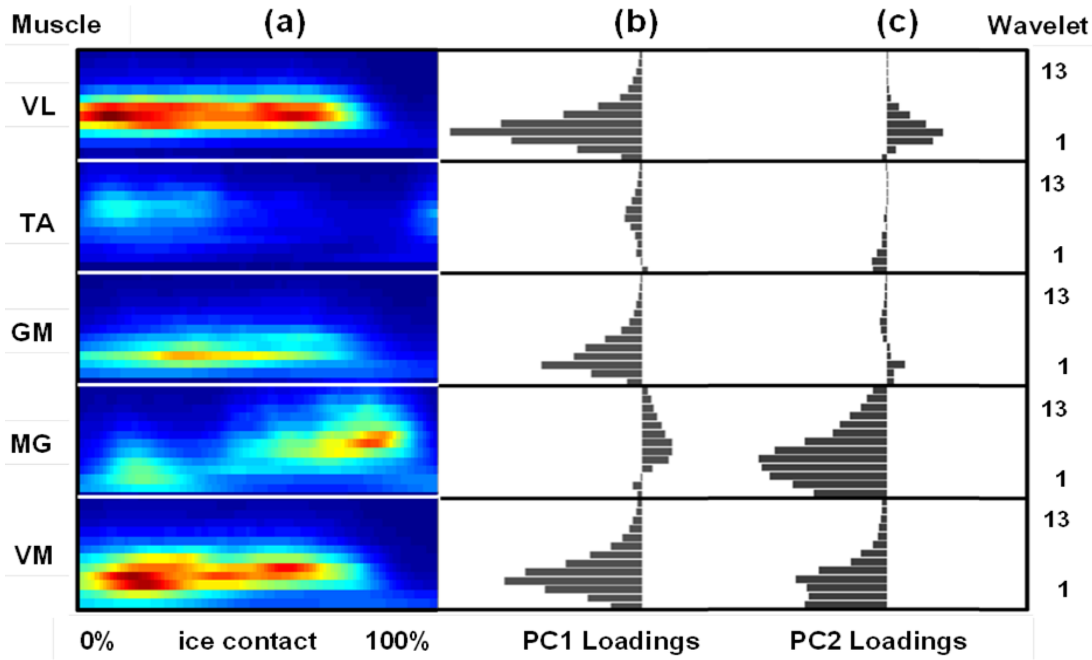

Figure 1. (a) Multi-muscle pattern representing EMG power in time-frequency space, (b) PC loadings of the five muscles on PC1 and (c) PC loadings of the five muscles on PC2. Each bar represents the contribution of EMG power towards the PC vectors.

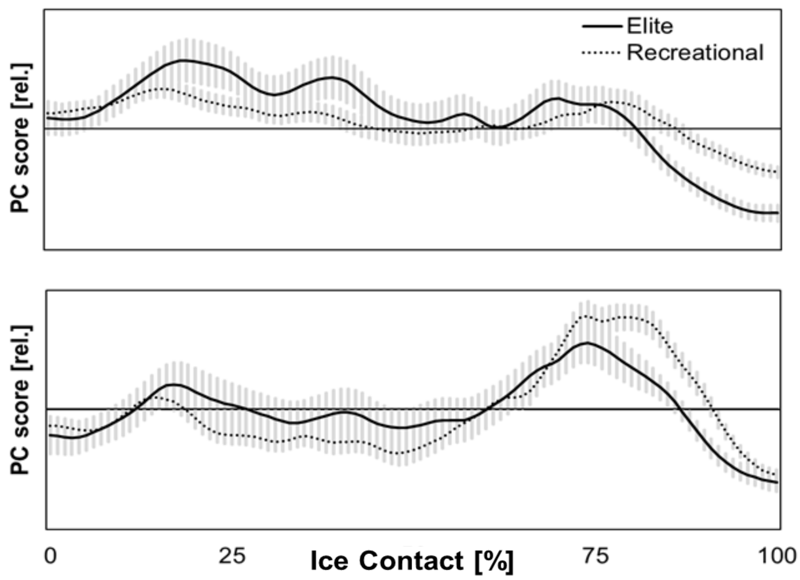

Figure 2. Averaged waveforms representing PC1 scores (top) and PC2 scores (bottom) of the elite and recreational group. Vertical lines represent standard deviations.

DISCUSSION: The goals of this study were first, to identify principal muscle activation patterns during accelerative hockey skating, and subsequently, to classify skill levels of players based on principal muscle activation patterns.

Activation of hip abductor muscles, combined with rapid onset of activation of the knee extensors was the primary muscle activation strategy during accelerative skating. This reflects the characteristic strategy for optimal power production during a sprint start, initiating the movement with a low centre of mass, and rapidly abducting the hip and extending the knee to achieve forward propulsion of the centre of mass (Harland & Steele, 1997). Inverse activation of VM and VL was a secondary feature of muscle co-ordination during skating acceleration. As the ratio between VM and VL has been shown to be important in knee stabilisation (Pal et al., 2012), inverse co-ordinations of the knee extensors may provide the knee with greater mechanical stability to counteract the large applied loads during explosive ice hockey acceleration strides, particularly when the leg is abducting and large pressure is being applied to the medial aspect of the skate.

This study saw significant classification of ice hockey skill levels based on the above principal patterns of muscle activity, where over 83% of all acceleration strides were classified according to the correct skillset. This suggests there are distinct differences in the way elite and recreational hockey players increase their speed on the ice. Expressing PC scores in the original coordinate space revealed hip-knee extensor activity to be the dominant strategy in elite level hockey skating. Conversely, recreational players demonstrated greater reliance on an ankle plantar flexor strategy during the latter propulsive portion of the ice contact phase, to achieve a powerful stride.

Classification and functional interpretation of muscle coordination is important for athletes and coaches to understand differences in muscle recruitment strategies across skill levels, and monitor changes that result from training. From this, important coaching implications were revealed: the determination of the muscles that should be trained, and the identification of strategies that are required, both of which are crucial to skate at the highest level.

CONCLUSION: Pattern recognition techniques applied to EMG data revealed changes in muscle activation strategies that are capable of discriminating elite from recreational athletes. These changes lead to better performance. The high classification rate indicated the significance of the differences of the muscle recruitment strategy. The differences could thus be explicitly visualized and confidently interpreted as a more efficient use of the hip-knee extensor activity and less ankle plantar flexion strategy by skilled athletes. Future research should focus on a reduced sensor set, incorporating only the sensors which capture the trade-off between hip-knee and ankle strategy during hockey skating, whilst maintaining a significant classification rate. This would be greatly beneficial for athlete specific monitoring during field tests.

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