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EMG-based lumbosacral joint compression force prediction using a support vector machine

Simon S.W. Li[a], Carlin C.F. Chu[b], Daniel H.K. Chow[c,*]

[a] Department of Health and Physical Education, The Education University of Hong Kong, Hong Kong
[b] School of Science and Technology, The Open University of Hong Kong, Hong Kong
[c] Department of Health and Physical Education, The Education University of Hong Kong, 10 Lo Ping Road, Tai Po, New Territories, Hong Kong

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ABSTRACT

Electromyography-assisted optimization (EMGAO) approach is widely used to predict lumbar joint loads under various dynamic and static conditions. However, such approach uses numerous anthropometric, kinematic, kinetic, and electromyographic data in the computation process, and thus makes data collection and processing complicated. This study developed an electromyography-based support vector machine (EMGB_SVM) approach for predicting lumbar spine load during walking with backpack loads. The EMGB_SVM is simple and uses merely the electromyographic data. Anthropometric information of 10 healthy male adults as well as their kinematic, kinetic, and electromyographic data acquired during walking exercises with no-load and with various backpack loads (5%, 10%, 15%, and 20% of their body weight) were used as the inputs of a biomechanical model, which was then used for predicting the lumbosacral joint compression force. The efficacy of the EMGB_SVM was investigated by comparing the force profiles obtained using this model with those obtained using the current EMGAO approach. On average, the EMGB_SVM obtained deviations in the peak and minimum forces of −3.3% and 5.1%, respectively, and a root mean square difference in the force profile of 7.5%. The EMGB_SVM is a comparable estimator in terms of its slight bias, favourable consistency, and efficiency at predicting the lumbosacral joint compression force.

1. Introduction

Biomechanical spinal models have been used to estimate joint loads and muscle forces [1]. Electromyography-assisted optimization (EMGAO) approach is widely used to predict lumbar joint loads under various dynamic and static conditions [2–6]. EMGAO approach [3], that does not require the measurement of trunk orientations by affixing anatomical markers at the lower back, is specifically useful for predicting lumbar joint loads during walking with backpack loads. However, current EMGAO approach uses numerous anthropometric, kinematic, kinetic, and electromyographic data in the computation process, and thus makes data collection and processing complicated [3,5]. The incorporation of important aspects and neglect of unimportant aspects are more of an art than a science. In general, however, simpler is better [7]. Thus, development of a simple model that is EMG-based, empirically validated, and most importantly can generate comparable approximations to real spine loading profiles is worthwhile, and such a model would be a useful tool.

Support Vector Machines (SVMs) have been demonstrated to have superior performance to other machine learning tools for small- to medium-size problems. Strongly advocated by Vapnik [8], SVMs have become a popular tool for solving nonlinear regression problems because of their superior generalizability for predicting unseen data. The model building approach commonly used in machine learning tools (such as neural networks, linear/nonlinear regression, and regression trees) is to minimize the empirical error. Thus, the constructed mathematical function aims to produce a numerical output with minimal deviation from the observed empirical outcome. This approach is named empirical risk minimization (ERM). However, a small empirical error does not guarantee favourable generalization ability when the model is applied to unseen data. By contrast, an SVM handles a problem by using the structural risk minimization (SRM) approach, which aims to minimize the upper bound of the generalization error. The SRM approach avoids overfitting of the empirical data by balancing model complexity and the training data fit. Furthermore, the SVM is claimed to be highly adaptive to the modeling of nonlinear relationships with the usage of a kernel trick; this trick implicitly

* Correspondence author.
E-mail addresses: ccfchu@ouhk.edu.hk (C.C.F. Chu), danielchow@eduhk.hk (D.H.K. Chow).

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transforms lower-dimensional input data into a higher-dimensional feature space for effective inspection of the underlying nonlinear relationship. Consequently, an SVM tends to have higher prediction performance in numerous circumstances [9].

The predictions of lumbar joint compression loads (but not for shear forces) obtained using different biomechanical models are relatively similar for various dynamic activities [10]. The present study aimed to evaluate an EMG-based support vector machine (EMGB_SVM) approach using only the EMG values representing the trunk muscle activity patterns for predicting lumbosacral joint compression force during walking with a backpack load.

2. Methods

2.1. Input data and experimental protocol

Anthropometric, kinematic, kinetic, and electromyographic data were collected (in a previous study [11]) to investigate the effects of a backpack load on trunk muscle activation and lumbosacral joint loading in 10 healthy men (mean age: 23 ± 2.8 years, body mass: 69.9 ± 9.0 kg, and height: 1.73 ± 0.07 m) while walking with various backpack loads (0%, 5%, 10%, 15%, and 20% body weight). The number of healthy men recruited was based on a previous study in a modified EMG-based handgrip force prediction using a learning machine [12]. A brief summary of the experimental protocol was described as below. After the anthropometry measurements were taken, participants were instructed to practice the walking exercise in their preferred speed with and without carrying a backpack load along a walkway pre-set in the laboratory. Then, they were equipped with fifteen anatomical markers attached to their lower bodies and twelve EMG sensors attached to the identified surfaces of trunk muscle. The participants walked barefoot with a backpack load at their preferred speeds (mean = 1.28 ± 0.09 m/s) along a walkway embedded with three force platforms carrying various backpack loads. Each participant performed three successful trials for each backpack load condition. Fifteen walking exercises (5 backpack load conditions x 3 trials) were performed in random order. Prior to conducting the walking trials, each participant performed twelve 3-second maximal voluntary contraction activities (three trials for each activity: bent sit up, back lift pull, trunk extension, and shoulder extension) and a static trial with two additional anatomical markers attached to the pelvis for calibrating the location of the lumbosacral joint center. Participants were allowed to rest for 1–2 min between two consecutive experimental trials and 5 min after finishing an entire set of walking or maximal voluntary contraction exercise. The duration of the experiment for each participant's visit was around 90 min. Lower body movements, ground reaction forces, and trunk muscle activity were captured using a synchronised system with eight-camera motion analysis (Qualisys, Gothenburg, Sweden), a force platform (Model 4060-10, Bertec Corporation, Columbus, OH, USA), and a wireless surface EMG system (Trigno, Delsys Inc., Boston, MA, USA) at sampling rates of 100, 2000, and 2000 Hz.

2.2. Electromyography-assisted optimization (EMGAO) approach

An EMGAO approach integrating the formulations established by Cholewicki et al. [3] and Gagnon et al. [5] was employed as the baseline biomechanical model used to predict the lumbosacral joint compression force during walking with backpack loads of 0%, 5%, 10%, 15%, and 20% BW. The detail computational processes have been reported in a previous study [11] and its results were used as data inputs to this study.

2.3. EMG-based support vector machine (EMGB_SVM) approach

SVM is able to identify various features of surface EMG activation patterns produced by six forearm muscles and provides very accurate predictions of handgrip force with both trained and untrained data [12]. This study employed the EMG values of the six pairs of bilateral trunk muscles (rectus abdominis, external oblique, internal oblique, latissimus dorsi, thoracic erector spinae, and lumbar erector spinae) for predicting the lumbosacral joint compression force during walking by using the SVM approach.

The epsilon-insensitive SVM (ε-SVM) was used to model the lumbosacral joint compression force in this study. The objective of this SVM is to find a function f(x) (the prediction of lumbosacral joint compression force based on SVM approach) in the original input dimension (the attributes of the 12 normalized EMG values of trunk muscle activation patterns) that has at most a deviation (margin) of ε from the actually obtained target y (the lumbosacral joint compression force estimated by the EMGAO approach). To ensure the existence of the solution, the ε deviation constraint is relaxed by introducing the 'soft margin' concept. The soft margin is implemented through the slack variables ξ and ξ^*, which impose a penalty cost when the ε deviation setting is not met.

The prediction function f(x) is defined as

$$f(x) = w \cdot \phi(x) + b \tag{1}$$

where w represents the weight vector, $\phi(x)$ maps the lower-dimensional input vector x to a higher-dimensional feature space, and b is a bias constant. The loss function of ε-SVM is

$$\text{Loss} = \begin{cases} 0 & \text{if } |y - f(x)| \le \varepsilon \\ |y - f(x)| - \varepsilon & \text{otherwise} \end{cases} \tag{2}$$

The optimal w can be obtained by solving the following primal optimization problem:

Minimize:

$$\frac{1}{2}||w||^2 + C\sum_{i=1}^{l}\left[\xi_i + \xi_i^*\right]$$

Subject to:

$$y_i - w \cdot \phi(x) + b \le \varepsilon + \xi_i$$

$$w \cdot \phi(x) + b - y_i \le \varepsilon + \xi_i^*$$

$$\xi_i, \xi_i^* \ge 0 \tag{3}$$

where l is the number of data points and ξ_i and ξ_i^* represent the magnitude of the soft margin outside the ε deviation, respectively. According to this formulation, only the data points outside the ε-insensitive region are of concern. These data points are regarded as support vectors.

The aforementioned primal can be solved more effectively under a primal-dual setting. By using the kernel trick, f(x) can be obtained without directly operating $\phi(x)$ and calculating the weight vector w. The solution of f(x) can then be reformulated as

$$f(x) = \sum_{i=1}^{l}\left(\alpha_i - \alpha_i^*\right)k(x, x_i) + b \tag{4}$$

where α_k and α_k^* are dummy variables generated using the Lagrange multipliers method; x_i is the ith data point, and K(x, x_i) is the result of the kernel function. The kernel function performs implicit higher-dimensional mapping and ensures the adaptability of the nonlinear relationship. The Radial Basis Function (RBF) kernel is employed in this paper:

$$k\left(x_j, x_k\right) = e^{\left(-||x_j - x_k||^2\right)} \tag{5}$$

The dual problem setting used to determine the model parameters is as follows:

Maximize:

$$-\frac{1}{2}\sum_{i,j=1}^{l}\left[\left(\alpha_i-\alpha_i^*\right)\left(\alpha_j-\alpha_j^*\right)k\left(x_i,x_j\right)\right]$$
$$+\sum_{i=1}^{l}\left[y_i\left(\alpha_i-\alpha_i^*\right)-\varepsilon\left(\alpha_i-\alpha_i^*\right)\right]$$

Subject to:

$$\sum_{i=1}^{l}\left(\alpha_i-\alpha_i^*\right)=0$$
$$0\le\alpha_k\le C$$
$$0\le\alpha_k^*\le C \tag{6}$$

C is a constant controlling the magnitude of the penalty cost for the soft margin. The dual problem can be solved effectively using the Karush–Kuhn–Tucker (KKT) method. The subscript k denotes the index of all data points (i.e. k = 1, 2, 3, …, n).

The corresponding KKT conditions are

$$\alpha_k(\varepsilon+\xi_k-y_k+f(x_k))=0$$
$$\alpha_k^*\left(\varepsilon+\xi_k^*-y_k+f(x_k)\right)=0$$
$$\xi_k(C-\alpha_k)=0$$
$$\xi_k^*\left(C-\alpha_k^*\right)=0 \tag{7}$$

A K-fold cross validation statistical evaluation method was adopted to evaluate the performance of SVM on unseen data [13]. It is one of the most commonly used resampling techniques to reliably evaluate the performance of a machine learning model.

2.4. Data reduction and statistical analysis

All data filtering, computation, and optimization processes were implemented using MATLAB 2016b software (MathWorks, Inc., Natick, MA, USA). The durations of gait cycles of each walking exercises for individual participants were different, thus all force profiles were time-normalized to 101 points for the applicability of comparisons and evaluations in both the time and magnitude domains. The root mean square difference (RMSD) of the force profiles predicted using the EMGB_SVM approach from the EMGAO approach was calculated using

$$RMSD_{L.P.T}=\sqrt{\frac{1}{101}\sum_{DD=1}^{101}\left(\frac{EMGB\_SVM_{L.P.T.D}-EMGAO_{L.P.T.D}}{EMGAO_{L.P.T.D}}\right)^2} \tag{8}$$

where

L = backpack load of 0, 5, 10, 15, or 20% BW;
P = participant 1, 2, …, 10;
T = trial 1, 2, or 3;
D = data point 1, 2, …, 101 of an individual force profile.

The peak and minimum compression forces (generated in each gait cycle) predicted using the EMGB_SVM and EMGAO approaches were also computed.

The data collected under various trials and loading conditions for individual participants were highly correlated within the context of repeated measurements. Thus, this study adopted a repeated measure ANOVA as the base model for all statistical analyses. One-way repeated-measure ANOVA was used to analyze the effect of backpack load on the RMSD of the force profile, whereas two-way repeated-measure ANOVA was employed to analyze the effect of backpack load and side (peak and minimum forces generated during the left and right foot loading response phases) on the peak and minimum forces of the force profile. The one-sample *t*-test was used to analyze the deviations of the peak and minimum forces (generated in each gait cycle) predicted by EMGB_SVM from those predicted by EMGAO, and Shapiro–Wilk test was employed to justify the assumption of normality for all experimental data sets (SPSS version 24.0, IBM Inc., Chicago, IL, USA). The statistically significant level was set at $p = 0.05$.

3. Results

The lumbosacral joint compression force profiles predicted using the EMGAO and EMGB_SVM approaches for walking exercise under various backpack loading conditions were determined on basis of the experimental dataset (Fig. 1).

One-way repeated-measure ANOVA confirmed that backpack load did not significantly affect ($p = 0.358$) the RMSD compared with EMGAO approach, and the overall mean RMSD of the compression force profiles obtained using the EMGB_SVM approach was 7.5 ± 3.7% (Table 1).

The average peak force predicted using the EMGAO and EMGB_SVM approaches was 1260–1671 N and 1231–1599 N, respectively, and the deviations (underestimations) of the average peak force predicted using the EMGB_SVM approach from EMGAO were 29–76 N (Table 2). The average minimum force predicted using the EMGAO and EMGB_SVM approaches was 61–84 N and 64–91 N, respectively, and the deviations (overestimations) of the average peak force predicted using the EMGB_SVM approach from EMGAO were 3–5 N (Table 2).

Two-way repeated-measure ANOVA confirmed the absence of significant side ($p = 0.497$), load ($p = 0.190$), and interaction

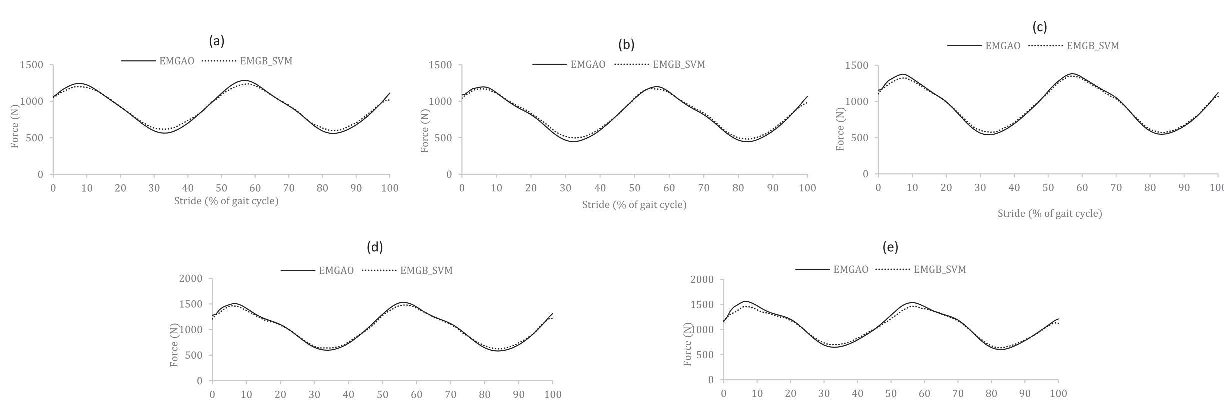

Fig. 1. Pooled mean lumbosacral joint compression force profiles (10 participants × 3 trials), obtained using the EMGAO and EMGB_SVM approaches, of an identified stride (gait cycle) under backpack load of (a) 0% BW, (b) 5% BW, (c) 10% BW (d) 15% BW, and (e) 20% BW.

Table 1
Pooled means, SDs, and results of statistical tests of the RMSD of lumbosacral joint compression force profiles, obtained using the EMGB_SVM approach compared with the EMGAO approach for all participants.

RMSD (%)	Backpack Load (% of body weight)					Overall	One way repeated measure ANOVA
	0	5	10	15	20		
Mean	7.2	8.7	5.7	7.1	8.8	**7.5**	$p = 0.358$
SD	3.4	3.0	1.1	3.3	5.9	**3.7**	
Shapiro–Wilk normality test	$P > 0.05$ for all data sets						

Bold value = mean of all pooled means (SDs).

Table 2
Pooled averages (SDs) of peak and minimum lumbosacral joint compression force magnitudes for each backpack load, predicted using the EMGAO and EMGB_SVM approaches. Left and right indicate the peak force during the left and right loading response phases, respectively.

Mean lumbosacral joint compression force (N)		Side	Backpack Load									
			0% BW		5% BW		10% BW		15% BW		20% BW	
			Peak	Min	Peak	Min	Peak	Min	Peak	Min	Peak	Min
Modeling Approach	EMGAO	Left	1260 (75)	81 (20)	1247 (109)	63 (12)	1370 (108)	73 (11)	1542 (147)	79 (16)	1671 (139)	84 (21)
	EMGB_SVM		1231 (74)	84 (21)	1217 (82)	66 (13)	1326 (104)	77 (12)	1487 (134)	83 (15)	1599 (146)	91 (16)
	Difference		**−29**	**3**	**−30**	**3**	**−44**	**4**	**−55**	**4**	**−72**	**5**
	EMGAO	Right	1324 (111)	76 (18)	1237 (80)	61 (12)	1401 (107)	73 (12)	1571 (132)	77 (16)	1659 (164)	81 (14)
	EMGB_SVM		1263 (124)	80 (18)	1203 (59)	64 (12)	1366 (102)	76 (13)	1517 (128)	80 (17)	1583 (163)	86 (14)
	Difference		**−61**	**3**	**−34**	**4**	**−35**	**3**	**−54**	**3**	**−76**	**5**

Bold value = difference between values of EMGAO and EMGB_SVM.

Table 3
Pooled averages, SDs, and results of statistical tests of the deviation of the peak lumbosacral joint compression force magnitude, obtained using the EMGB_SVM and EMGAO approaches for all participants. Left and right indicate the peak force during the left and right loading response phases, respectively.

	Deviation compared with EMGAO approach (%)									
Side	Left (peak force generated during left foot loading response phase)					Right (peak force generated during right foot loading response phase)				
Backpack load (% of body weight)	0	5	10	15	20	0	5	10	15	20
Mean	−2.3	−2.3	−3.2	−3.4	−4.3	−4.7	−2.6	−2.5	−3.4	−4.6
SD	2.2	2.7	1.6	2.0	2.8	2.5	2.3	0.7	2.0	3.9
Overall	Mean: −3.1 SD: 2.4					Mean: −3.6 SD: 2.6				
	Mean: −3.3 SD: 2.5 (One-sample t-test: mean deviation = 0, $p < 0.001$)									
Shapiro–Wilk normality test	$P > 0.05$ for all data sets									
Two way repeated measure ANOVA	Side					$p = 0.497$				
	Backpack load					$p = 0.190$				
	Side*backpack load					$p = 0.079$				

($p = 0.079$) effects on the deviations of the peak force compared with the EMGAO approach, and the predictions obtained using the EMGB_SVM approach significantly underestimated ($p < 0.001$) the peak lumbosacral joint compression force by an average of 3.3 ± 2.5% (Table 3).

Two-way repeated-measure ANOVA confirmed the absence of significant side ($p = 0.810$), load ($p = 0.197$), and interaction ($p = 0.576$) effects on the deviations of the minimum force compared with the EMGAO approach, and the predictions obtained using the EMGB_SVM approach significantly overestimated ($p < 0.001$) the minimum lumbosacral joint compression force by an average of 5.1 ± 2.9% (Table 4).

4. Discussion

In this study, the lumbosacral joint compression forces predicted using the EMGB_SVM approach were compared with those obtained using the EMGAO approach. The EMGB_SVM approach predicted similar and comparable force profiles.

Surface EMG measurement reflects the muscle activation pattern and is a crucial neurological signal when estimating muscle and mechanical forces [11,12]. Studies have obtained efficient EMG-based hand grasp force predictions using the SVM approach [12,14,15]. Such studies have demonstrated that the SVM approach favourably approximates mechanical forces as well as the hand orientation and torque from muscle activity levels by using surface EMG measurements. Because it is EMG-based, the SVM approach is sensitive to the muscle recruitment patterns employed by individuals when they are performing tasks [12]. However, its major shortcoming is its inability to meet the biomechanical requirements of moment equilibrium constraints at certain spinal levels. This shortcoming resulted in underestimations of lumbar spinal compression loads compared with the EMGAO approach.

K-fold validation was employed in this study to empirically analyze the performance of EMGB_SVM when applied to unseen data. The cross validation method was processed in accordance with a sequential computational operations where $K = 10$ was set for this study. First, the data were pooled together from all participants, then randomly partitioned into 10 nonoverlapping sets. Second, each set was reserved as an unseen dataset and a model was constructed using the remaining 9 sets. Third, a prediction was made on the reserved set by using the constructed model. Fourth, the

Table 4
Pooled averages, SDs, and results of statistical tests of the deviation of the minimum lumbosacral joint compression force magnitude, obtained using the EMGB_SVM and EMGAO approaches for all participants. Left and right indicate the peak force during the left and right loading response phases, respectively.

	Deviation compared with EMGAO approach (%)									
Side	Left (minimum force generated during left foot loading response phase)					Right (minimum force generated during right foot loading response phase)				
Backpack load (% of body weight)	0	5	10	15	20	0	5	10	15	20
Mean	4.0	5.4	5.7	5.3	5.7	4.5	6.1	4.4	4.0	6.4
SD	1.7	1.9	3.1	3.5	1.8	3.2	3.8	2.8	3.4	2.9
Overall	Mean: 5.2 SD: 2.5					Mean: 5.1 SD: 3.3				
	Mean: 5.1 SD: 2.9 (One-sample t-test: mean deviation = 0, $p < 0.001$)									
Shapiro–Wilk normality test	$P > 0.05$ for all data sets									
Two way repeated measure ANOVA	Side					$p = 0.810$				
	Backpack load					$p = 0.197$				
	Side*backpack load					$p = 0.576$				

Bold value = mean of all pooled means (SDs).

results were averaged from the 9 sets to act as an objective measure of the model's performance when applied to unseen data. The prediction errors obtained between the EMGAO and EMGB_SVM approaches are dependent on the nature of the tasks performed and the constraints introduced in the computation process. The EMGB_SVM approach in this study underestimated the peak compression forces by approximately 3%, possibly indicating the error in the predictions for walking with a backpack load.

The consistency and efficiency of the peak and minimum lumbosacral joint compression forces predicted using the EMGB_SVM approach met the requirements of a good estimator [16]. On average, the standard errors of the deviations for the EMGB_SVM approach was relatively small for both peak and minimum forces predictions (lower than 1%), and the peak and minimum forces predicted using the EMGB_SVM approach were comparable to that predicted using the EMGAO approach. The prediction using the EMGB_SVM approach was consistent and efficient, and even though there was a small amount of bias, the results serve as a favourable estimator of the peak and minimum lumbosacral joint compression force estimations.

A previous study [17] compared the predictions between an EMGAO and two non-EMG based biomechanical models, single and double linear optimization approaches for lumbar spine loading during walking with backpack loads. The study reported that on average, the peak lumbosacral joint compression forces were underestimated by 5.1% and 19.2%, respectively, and the RMSD in force profiles were 16.2% and 25.4%, respectively. Comparing these findings with the predictions by EMGB_SVM (underestimation of 3.3% in peak force and 7.5% of RMSD in force profile), EMGB_SVM provided a better estimations in both peak force and force profile.

The complexity of an EMGAO approach is a result of the formulation of an EMG–force relationship. The sophisticated EMGAO approach [2,3] adopts a non-linear EMG–force relationship and incorporates one variable (EMG value obtained during the walking trials) and three parameters (EMG values obtained under maximal voluntary contraction activities, muscle physiological cross-sectional area, and maximum muscle intensity). Previous studies reported that the complexity resulting from the consideration of surplus of parameters might not improve prediction accuracy [18–20]. The EMGB_SVM approach used only the EMG values and eliminated all other parameters, and thus enhanced the experimental procedure and data collection. The EMGB_SVM approach is of vital important in clinical application, especially for patients or even healthy individuals who could not provide valid anthropometric information about muscle parameters or perform the maximal voluntary contraction activities.

This study has several limitations. First, the walking exercise adopted in this study required low levels of tonic activation in the upper bodies, and thus the EMGB_SVM approach provides accurate estimation of lumbosacral joint compression force. Further study in high tonic activation, such as manual material handling in occupational tasks, is needed to generalize the EMGB_SVM approach. Second, only 10 healthy male adults were recruited in this study. The validation of EMGB_SVM approach to predict lumbosacral joint compression force in this study might not be extrapolated to a broader population. It is more appropriate, for further study, to include females and participants in other age groups so as to generalize the application of EMGB_SVM approach. Third, this study only validated the significant employment of EMGB_SVM approach to predict the lumbar joint loads during a specific task of walking with backpack loads, further justification on the generalization as well as clinical and occupational applications of such approach to other dynamic activities, such as during perturbed standing or sitting, or material handling tasks is needed. Fourth, this study did not focus on looking for the insight of correlation features based on principal component analysis (PCA) or canonical correlation analysis (CCA). The comparison of predictions, on the peak and minimum forces as well as the whole force profile, between the EMGAO and EMGB_SVM approaches was based the root mean square difference (RMSD) which was adopted in previous similar studies [3,12,17].

In conclusion, the EMGB_SVM approach is simple and efficient when predicting the lumbosacral joint compression force of walking with a backpack load between 0% and 20% body weight. Generalization and refinement of the EMGB_SVM approach might be worthwhile, including estimation of the mechanical load on various human joints during dynamic motions under backpack loads larger than 20% body weight, reflecting the recreational, occupational, and operational activities of hikers, workers, and soldiers, respectively.

Declaration of Competing Interest

None.

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Ethical Approval

Ethical approval was granted by the Institutional Review Board of the Education University of Hong Kong.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.medengphy.2019.09.009.

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