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Chapter 3

Automatically determining lumbar load during physically demanding work: an in-vivo validation study

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Submitted

Abstract

Several studies have proposed that a sensor-based system using inertial magnetic measurement units and surface electromyography is suitable for objectively and automatically monitoring the lumbar load during physically demanding work. However, the validity and usability of this system in the uncontrolled real-life working environment of physically active workers are still unknown. The objective of this study was to test the discriminant validity of an artificial neural network-based method for load assessment during actual work. Nine physically active workers performed work-related tasks while wearing the sensor system. The main measure representing lumbar load was the net moment around the L5/S1 intervertebral body, estimated using a method that is based on artificial neural network and perceived workload (measured with CR-10 rating scale). The hypotheses were (1) the lumbar load and perceived workload are higher during heavy tasks than during light tasks, and (2) the variation in moments during dynamic tasks is higher than during static tasks. The mean differences (MD) were tested using a paired t-test. During heavy tasks, the net moment (MD=64.3±13.5%, $p=0.028$) and the perceived workload (MD=5.1±2.1, $p<0.001$) observed was significantly higher than during light tasks. The lumbar load had significantly higher variations during dynamic tasks (MD=33.5±36.8%, $p=0.026$) and the perceived workload was significantly higher (MD=2.2±1.5, $p=0.002$) than during static tasks. It was concluded that the validity of this sensor-based system was supported, because the differences in the lumbar load were consistent with the perceived intensity levels and character of the work tasks.

Keywords: Physically active workers, low back pain, EMG, inertial motion units

3.1 | Introduction

Physically active workers sometimes can experience muscle and spinal overload while performing their physically demanding jobs (Ilmarinen, 2001). Such an overload is hypothesized to be due to a misbalance between the physical workload and the individual capacity of each worker (Wu & Wang, 2002). This misbalance may cause health problems among these workers, such as musculoskeletal disorders, like lower back pain (Coenen, et al., 2016; Jorgensen, et al., 2013; Holterman, et al., 2013; Andersen, et al., 2007; Bakker, et al., 2009). These problems usually result in the loss of productivity (Weerding, et al., 2005; Pransky, et al., 2005; Karpansalo, et al., 2002), loss of quality and safety (Ilmarinen, 2001; Varianou-Mikellidou, et al., 2019; Brouwer, et al., 2013), and absenteeism (Ilmarinen, 2001; Kenny, et al., 2008). Hence, to help prevent these health problems and promote sustainable employability, it is important to investigate and optimize the musculoskeletal load while performing physically demanding jobs (Nath, et al., 2017; Heerkens, et al., 2004; Costa-Black, et al., 2013).

There is a need for a device that can measure the individual working posture and related lumbar load objectively while performing a physically demanding job (Coenen, et al., 2014). Typically, this lumbar load is represented by the net moment around the center of the intervertebral body at spinal level L5/S1. Inertial motion capture systems are useful for monitoring the lumbar load of individuals in terms of 3D net moments and forces in the lower spine and for investigating the kinematics while working in industrial environments (Baten, et al., 1995, 2015, 2018; Kingma, et al., 2001; Dolan, et al., 1998; Valevicus, et al., 2018; Faber, et al., 2015; Xu, et al., 2012; Coenen, et al., 2014). Various methods have been developed to estimate the net moment in the lower back under known load-handling conditions (de Looze, et al., 1992; Baten, et al., 1995, 1996, 2000, 2015; Faber, et al., 2015). All of these methods use 3D body segment kinematics data acquired using marker-based motion analysis systems. By using e.g., the reaction forces exerted on the hands or from detailed information on the load and measured or known external forces exerted on the human body. Using inertial magnetic measurement units (IMMUs) allows for more freedom in 3D kinematics assessments in comparison to marker-based motion analysis systems (Baten, et al., 2007). However, the need to measure all the forces exerted on the human's lower body e.g., by force plates embedded in the lab floor severely limits their practical applications. A more mobile alternative is to use instrumented shoes that measure ground reaction forces while walking around (Schepers, et al., 2007, 2010; Baten, et al., 2015; Faber, et al., 2015). This system provides more freedom of movement but requires that no other external forces be exerted on the lower body (e.g., by leaning against a table or supporting the load being handled). Additionally, the relatively large weight of these shoes and their current design make them less usable in practice. Therefore, several alternative methods for estimating lumbar load assessment were that do not require force assessment were developed. In this study, an artificial neural network (ANN) based method was developed to estimate 3D net moments (L5/S1) from electromyography (EMG) and trunk kinematics. It is trained in the initial part of each session from a limited set of calibration trials (Baten, et al., 1995, 1996, 2000, 2007, 2015). Generally, ANNs are supervised mode target net moments for the calibration trials become available by direct estimation using a linked segment model (LSM-based method; Kingma, et al., 2001; Baten, et al., 1996) scaled by the length and weight of the subject. Methods based on the LSM are driven by kinematic data from IMMUs on the trunk and arms. Details on the known loads handled during the calibration trials are required. Therefore, in the actual trials, a trained ANN-based method was used to estimate the net moments from the IMMU kinematics data and EMG data of a subject during actual work.

ANN-based methods have been evaluated in lab studies for ambulatory movement analysis, and the results were found to be promising (Baten, et al., submitted; Kingma, et al., 2001). This system is considered potentially useful for monitoring human postures and movement of workers while they are performing their jobs. As well as for estimating the mechanical workload and individual muscle response to this load while performing physically demanding jobs (Baten, et al., 1996, 2000, 2015; Valevicus, et al., 2018). Ultimately, this may represent a tool that provides workers and ergonomists with instant feedback, which may contribute to preventing overload. However, the validity and usability of this system in the uncontrolled real-life working environment of physically active workers are still unknown.

The objective of this study was to test the discriminant validity of an ANN-based method for load assessment during actual work. The research questions were: (1) what is the correlation between the ANN-based method and the LSM-based method to estimate lumbar load? (2) Can this ANN-based method detect differences in load intensity and perceived workload during light and heavy tasks? (3) Can the system detect differences in load-variability during static and dynamics tasks? And (4) can the system detect (a)symmetrical lumbar load difference around the anterior-posterior, mediolateral and longitudinal axes?

3.2 | Methods

3.2.1 | Subjects

A total of 23 subjects participated in this study, all of whom were physically active workers recruited through flyers distributed within selected companies. These selected companies were active in medical disinfection care, industrial chemical cleaning, and technical services. All subjects were informed about the study through an information letter and received a verbal explanation before the start of the study. The inclusion criterion was being a physically active worker aged between 18 and 67. The exclusion criteria were having any cardiovascular diseases; using pacemakers or other vital electronic devices; having high levels of pain or injuries in the back, shoulders, or upper extremities; or being at an advanced stage (around 20 weeks) of pregnancy. The Medical Ethics Committee of the University Medical Center Groningen, the Netherlands, issued a waiver for this study, stating that it does not involve medical research according to the Dutch law (M17.208063), and all subjects signed an informed consent form.

3

3.2.2 | Study design and procedures

Each session with every subject comprised three phases: (1) trials for upper body segment calibration, (2) trials with known loads for supervised training and training quality validation, and (3) trials illustrating performance during a set of work-related tasks.

In phase 1 the subjects were asked to perform a set of movements while wearing IMMUs surface electromyography (sEMG) to calibrate the IMMUs to the orientation of the IMMUs relative to the body segments. The set contained 90° trunk bending, 45 ° trunk lateroflexion, 45° trunk rotation, 45° shoulder flexion, and 90° shoulder abduction. This was repeated five times and followed by three seconds of standing in a neutral anatomic position with the arms hanging next to the body with thumbs pointing forward. The resulting segment calibration parameters were used to translate all sensor casing kinematics within a session to body segment and joint kinematics.

To test correlation between the ANN-based method and the LSM-based method (question 1), in phase 2 trunk bending, flexion, and rotation movements were performed without (0 kg) and with holding a load of 6 and 10 kg in the hands. For all trials, ‘target’ net lumbar moments (spinal level L5/S1) were calculated from only the upper body kinematics applying a LSM-based method (Baten, et al 1996; Kingma, et al. 2001). Subsequently, the ANN-based estimator was trained to estimate the target moment data driven by EMG plus the kinematics data for the trials with 0 and 10 kg. Then the trained ANNs were applied to estimate the net moment for the trial of 6 kg driven by EMG and kinematics data of this trial. The resulting net moment data estimates were validated against the target net moment data for the corresponding 6 kg trial. This direct comparison provided a quantitative assessment of the estimation accuracy. Finally, the ANN-based estimator was trained for all the bending, flexion and rotation movements and for all three weights (0, 6 and 10 kg) to be used for application in phase 3. For all training, optimal settings for ANN-based method have been used. Those settings were determined beforehand in a sensitivity study by Baten, et al. (submitted) for many combinations of the ANN settings, input data selection and preparation method parameters. This resulted in a standard feed-forward neural network with one hidden layer with 31 nodes in the hidden layer as well as sigmoid input transfer functions.

Questions 2, 3 and 4 about the discriminant validity of the ANN-based method were explored in phase 3. The subjects performed job-specific work-related tasks for 5–10 min of different intensity and dynamically were performed. For alle these tasks net moment curves were estimated using the ANN-based network trained at the end of phase 2. Additionally, these tasks were ranked according to the checklist of physical workload (Peereboom & de Langen, 2012). Before the start of the measurements, the subjects received a questionnaire to identify the daily tasks and the frequency, duration, and perceived workload per task. All subjects ranked tasks according to the load, starting with the heaviest task (Peereboom & de Langen, 2012). From the list of work-related tasks, four tasks were defined, which may vary from one individual to another: (1) a light task with a low workload on the lumbar muscles, (2) a heavy task with a high workload on the lumbar muscles, (3) a static task (working with the lumbar region in the same posture), and (4) a dynamic (lifting) task in different (spinal) working postures (Arbo, 2013; Dutch Ministry of Social Affairs and Employment, 2017). To explore question 2 and 4, the task with the highest workload was selected as a heavy task, and the task with the lowest workload was selected as a light task. Net moment data curve appearances were discussed with respect to the trial perceived workload. To explore question 3 and 4, the criterion for the static task was that the lumbar region is held in the same posture or joint position for at least 4 s throughout the task with low variations in the lumbar posture when changing the posture (ISO standard 11226:2000; Arbo, 2013). The criteria for the dynamic task were as follows: the task must be a lifting one and the lumbar spine should vary in posture. After every task, the subjects were asked to rate the perceived workload of the three tasks using Borg CR-10 rating scale, ranging from 0 to 10 (0=*not burdensome*, 10=*extremely heavy* (Borg, 1998).

3.2.3 | Materials

3.2.3.1 | Surface electromyography acquisition

All sEMG recordings were performed using a wearable sEMG instrument (Polybench Dipha; Inbiolab, Roden, the Netherlands). Bipolar electrodes (Covidien Kendall™ H124SG Ag/AgCl electrodes; Medtronic, Minneapolis, MN, USA) with an interelectrode distance of 2 cm (heart to heart) were placed on the longissimus thoracis muscle at L1 (±3 cm horizontal from L1) and the iliocostalis lumborum muscle at L2-L3 (±6.5 cm horizontal from L2-L3), along with a reference electrode placed at the processus spinosus of C7 (Roy, et al., 1995) (see Figure 3.1).

3.2.3.2 | Kinematics acquisition and net moment estimation

Six wired IMMUs (MVN Awinda; Xsens, Enschede, the Netherlands) were used to record 3D body segment kinematics. The IMMUs were placed on the sternum, upper and lower arms, and pelvis (sacrum; Baten, et al., 2000, 2015; Koopman, et al., 2018), as shown in Figure 3.1. The sample rate was 50 Hz. All IMMU data-acquisition procedures, as well as the translation of IMMU casing kinematics data to body segment and joint kinematics data, were performed with the FusionTools/XCM software suite (Roessingh Research and Development, Enschede, the Netherlands; Baten, 2015, 2018) using the Xsens application programming interface. Using the same software suite, EMG data preparation (amplitude estimation by smoothed rectification, intrapolated resampling to 50 Hz) and synchronization with IMMU data were performed. All load exposure estimations were also performed using this software suite, with both LSM-based and ANN-based method. As well the calculation of all the descriptive statistics of the net moment curves and root-mean-square error (RMSE) values and correlation coefficients, comparing the target and estimated net moments.

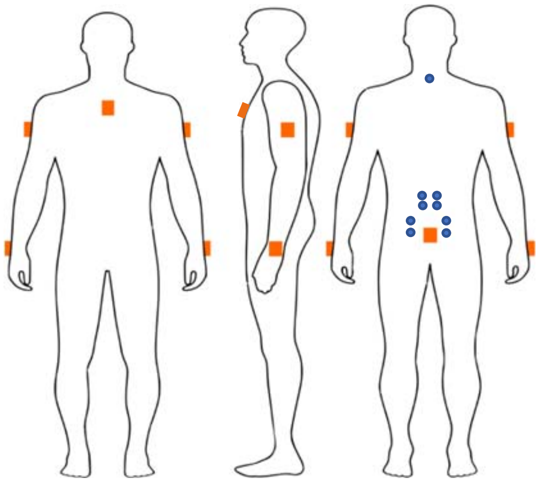

Figure 3.1 | The positioning of the sEMG electrodes and IMMUs on the body. The surface electromyography (sEMG electrodes, blue rounds) positioned on the longissimus thoracis muscle at L1 and the iliocostalis lumborum muscle at L2-L3 with a reference electrode placed at the processus spinosus of C7. The Inertial Magnetic Measuring Units (IMMUs, orange blocks) positioned on the sternum, upper and lower (left and right) arms, and pelvis (sacrum) with front (left), side (middle), and back view (right).

3.2.4 | Data analysis

To test the correlation between the ANN-based method and the LSM-based method (question 1), in phase 2 the main evaluation comprised a comparison of ANN-based estimated and target net moment trajectories in 3D. The primary outcome was the moment and RMSE at the moment magnitude (||M||, calculated through the net moment vector norm). Evaluation was performed for every rotation axis and net moment magnitude by means of visual inspection of data plots. And by evaluating RMSE values between the estimated and target moments and Pearson's correlation coefficient (r with $0.1<r<0.3$ indicating a small correlation, $0.3<r<0.5$ indicating a medium correlation, and $0.5<r<1.0$ indicating a strong correlation (Kristiansen, et al., 2019) and its squared value (r^2). Trunk bending is a movement in the mediolateral transverse (Y) axis, trunk lateroflexion is a movement in the anterior-posterior (X) axis and trunk rotation is a combined movement mainly in the longitudinal (Z) axis. If a strong correlation was found for these movements in these axes between the ANN-based method and the LSM-based method, the ANN-based method was of acceptable level.

In phase 3, the results of the questionnaire were categorized on the basis of the perceived workload, with 1 meaning a light task and 5 meaning a very heavy task (Peereboom & de

Langen, 2012). According to these scores, the tasks to test questions 2, 3 and 4 were selected. To test whether this sensor system can distinguish differences between intensity and variability of the estimated lumbar load, a discriminant validity analysis was performed. Primary parameters were mean, peak (max) and variation (deviation within a subject) of the net moment in the lumbar region and perceived workload (Borg CR-10) (Borg, 1998).

To explore if this ANN-based method can distinguish estimated lumbar load differences in intensity levels (question 3) differences between light and heavy tasks were analysed. The hypothesis was that during heavy tasks the mean net moments in the lumbar region were significantly higher. Additionally, the hypothesis that the perceived workload (Borg CR-10 score) of the heavy tasks were significantly higher than the light tasks was tested. The hypothesis of question 3 (variability level) was that the variability in net moments in the lumbar region were higher during dynamics tasks than during the static tasks.

To explore the (a)symmetrical character of working posturers, the movement direction of the moment around the anterior-posterior, mediolateral and longitudinal axes (question 4) was assessed. The direction of the net moment was divided in a positive and a negative movement direction; anterior-posterior with lateroflexion to the left (positive) and right (negative), mediolateral with flexion (positive) and extension (negative), longitudinal with rotation to the left (positive) and right (negative) axes. The hypothesis was that the tasks had asymmetrical character. These separated moment directions were tested with the same hypothesis described for question 2 and 3.

Questions 2, 3 and 4 were tested by firstly explore the distribution of the data using a Shapiro–Wilk test of normality and was considered to be normally distributed if $p \leq 0.05$. Normally distributed data between the tasks were assessed using a paired t-test and non-normally distributed data were also tested using the Wilcoxon signed-rank test. A difference of the net moment was significant when $p \leq 0.05$. The results are presented as the absolute and relative mean or mean difference (MD)±the standard deviation (SD). All statistical analyses were performed using IBM SPSS Statistics (version 25; IBM Corp., Armonk, NY, USA).

3.3 | Results

Out of the 23 workers who participated in this study, the data of 12 subjects were not useable because of a data-acquisition error in either the IMMUs or sEMG during essential trials. Moreover, the data of another two subjects performing dynamic and/or heavy tasks contained data-acquisition errors. Therefore, these 14 subjects were excluded from the analysis, leaving a set of data of nine subjects (eight males, one female): four medical cleaners, three maintenance engineers, and two chemical cleaners. Their mean age was 33.7±10.3 years, length 185±9 cm, and weight 93±12 kg. Eight subjects were right-handed, and one subject was left-handed.

3.3.1 | Question 1: Correlation ANN-based and LSM-based method

Table 3.1 shows the correlation between the ANN-based method and the LSM-based method. For one subject (subject 6), the data of the calibration movement with 6 kg were not usable and, hence, were not included in the mean results. These results differ per subject due to the individual character of the results. Calibration differs from one subject to another, which can be due to differences between the three calibration sets with three different weights or due to an unidentified event. This resulted in nonperfect calibration for subject 8, with overall medium to small correlations.

Strong correlations were observed in trunk bending (mean r^2=0.84±0.29) and lateroflexion (mean r^2=0.76±0.27). For both movements, one subject (subject 8) showed a small correlation ($r^2 \leq 0.12$), whereas the other subjects showed strong correlations ($r^2 \geq 0.72$). Strong correlations were also observed during trunk rotation in the longitudinal axis (r^2=0.51±0.28), although a medium correlation was observed in the anterior-posterior axis (r^2=0.47±0.28). Overall, the results were within the acceptable range (r>0.5).

Table 3.2 compares the RMSE values between the ANN-based method and the LSM-based method. These results indicate a mean estimation errors of 9.25±6.01 Nm, relative to the typical net moment ranges from 150 to 220 Nm (see Table 3.4).

Table 3.1 | ANN-based method performance in handling known loads.

			Subject										
Movement	**Axis**		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Mean**	**SD**
Bending	Y	r	0.97	0.98	0.96	0.97	0.98	-	0.96	0.35	0.98	0.89	0.22
		r^2	0.94	0.95	0.93	0.93	0.96	-	0.92	0.12	0.96	0.84	0.29
Lateroflexion	X	r	0.94	0.93	0.95	0.95	0.94	-	0.85	0.32	0.92	0.85	0.22
		r^2	0.89	0.87	0.91	0.90	0.88	-	0.72	0.10	0.84	0.76	0.27
Rotation	Z	r	0.63	0.23	0.84	0.84	0.81	-	0.76	0.38	0.92	0.68	0.24
		r^2	0.40	0.06	0.70	0.70	0.65	-	0.58	0.15	0.84	0.51	0.28

Shown are the correlation between the net moment at L5/S1 estimated with the ANN-based method and with the LSM-based method. Correlation is represented by the Pearson correlation coefficient (r) and determination coefficient (r^2) and are shown only for the axis of movement in each task (i.e. in the mediolateral axis (y) for the trunk bending tasks, in the anterior-posterior axis (x) for the lateroflexion tasks (y) and the longitudinal axis (z) for the rotation tasks respectively). Shown are individual values for each subject plus the mean and standard deviation (SD) over all subjects. No valid data were obtained for subject number 6 for reasons of partially missing data in the 6 kg trial.

3.3.2 | Question 2: Intensity

Table 3.3 shows the tasks per job according to the results of the questionnaire. All the subjects, except for one industrial cleaner, perceived the dynamic task as the heaviest task of their job. Small differences in the checklist for physical workload scores were observed, which were related to the diversity in the individual job description.

Table 3.3 | Tasks per job type, based on the results of the checklist for the physical workload.

Task perception	**Medical disinfect care**	**Technical services**	**Industrial chemical cleaning**
Light	Changing working clothing	Administration	Disassemble gas mask
Static	Assembly or lamination of surgical instruments	Tinkering under a machine	Cleaning chemical hazard suit
Heavy and dynamic	Carrying bins of 3 up to 10 kg	Moving (pushing and/or pulling) bin with wastewater of 1000 kg or carrying toolbox of 35 kg	Carrying bins of 5 up to 10 kg

In Table 3.4 presents the net moment per task together with the experienced workload of the tasks according to the subjects. During all the tasks, the mean net lumbar moment was 25.2±16.8 Nm, the mean peak moment was 179.5±152.9 Nm, and the mean variation was 15.5±11.5 Nm.

Table 3.4 | Net moments, load ranking, and perceived workload for each task.

Task perception	**Net moment (Nm)**			**Questionnaire load factor (1-5)**	**Perceived workload (Borg 0-10)**
	Mean	**Peak**	**Variation**		
Light task	18.7±8.1	166.4±195.5	13.0±10.6	1.0±0.0	0.9±0.8
Static task	26.3±19.2	153.5±106.1	13.7±9.9	3.6±1.3	3.8±1.6
Heavy and dynamic task	30.7±20.0	218.5±154.4	19.8±13.8	4.8±0.4	6.0±2.0

The questionnaire workload factor with 1=light work and 5=very heavy task. The experienced workload (Borg CR-10) according to the subjects with 0=not burdensome and 10=extremely heavy.

Table 3.5 summarizes the differences between light and heavy tasks presented for all subjects, with a typical example in Figure 3.2. It can be seen that the net moments estimated using the ANN-based method exhibit overall higher moments during heavy tasks with more variations than during light tasks. The differences in the mean net moment between light and heavy tasks were significant (MD=64.3±72.1%, p=0.028), whereas the other differences were not. The perceived workload was significantly higher during the heavy tasks than during light tasks (MD=5.1±2.1, p<0.001).

Table 3.5 | Light vs heavy tasks.

	Absolute [Nm]		**Relative (%)**		
Parameter	**MD±SD**	**[95% CI]**	**MD±SD**	**[95% CI]**	**p**
Mean	12.0±13.5	[1.7;22.4]	64.3±13.5	[8.9;119.8]	0.028
Peak	52.1±256.9	[-145.4;249.6]	23.9±117.6	[-66.5;114.2]	0.560
Variation	6.8±9.4	[-0.4;14.0]	52.1±71.8	[-3.1;107.3]	0.061

Shown are the absolute [Nm] and relative [%] differences between the light tasks and the heavy tasks through mean (MD), standard deviation (SD), and 95% confidence interval (CI) of these differences for the moment magnitude (||M||).

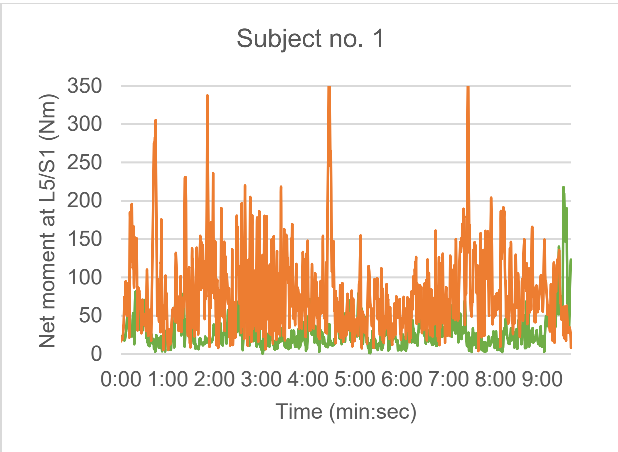

Figure 3.2 | Typical example of net moment curves during light (green) and heavy (orange) tasks (Subject 1).

3.3.3 | Question 3: Variation

Table 3.6 summarizes the differences between static and dynamic tasks presented for all subjects, with a typical example in Figure 3.3. It can be seen that the mean net moments of the magnitude estimated using the ANN-based method exhibit overall higher values during dynamic tasks with more variations than during static tasks. The difference in the variation between static and dynamic tasks was significant (MD=44.8±48.9%, *p*=0.025). The perceived workload was significantly higher during the dynamic tasks than during static tasks (MD=2.2±1.5, p=0.002).

Table 3.6 | Static vs dynamic tasks.

	Absolute [Nm]		Relative (%)		
Parameter	**MD±SD**	**[95% CI]**	**MD±SD**	**[95% CI]**	**p**
Mean	4.42±8.03	[-1.8;10.6]	16.8±30.6	[-6.7;40.4]	0.137
Peak	65.0±138.6	[-41.5;171.5]	42.3±90.3	[-27.0;111.7]	0.197
Variation	6.13±6.69	[1.0;11.3]	44.8±48.9	[7.2;82.4]	0.025

Shown are the absolute [Nm] and relative [%] differences between the static tasks and the dynamic tasks through mean (MD), standard deviation (SD), and 95% confidence interval (CI) of these differences for the moment magnitude (||M||).

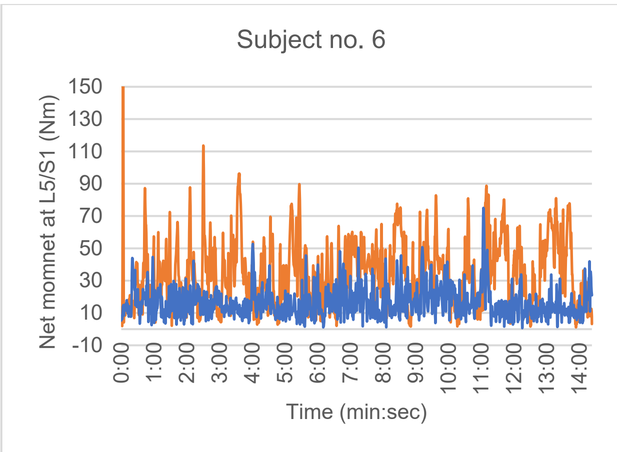

Figure 3.3 | Typical example of net moment curves during static (blue) and heavy (orange) tasks (Subject 6).

3.3.4 | Question 4: (a)Symmetrical lumbar load

Table 3.7 summarizes the differences between light and heavy tasks presented while taking into account the direction of the movement around the axis (e.g., flexion versus extension). Similar results of the intensity levels were observed as in Table 3.5. It was observed that the mean net moment is significantly higher during heavy tasks than during light tasks (MD≥92.3±105.4%, p≤0.030) as well as in the singular anterior-posterior axis (MD≥56.8±44.9%, p≤0.016). All the other differences were not significant.

Table 3.7 | Direction of the net moment around the axis of the light vs heavy tasks.

			Absolute [Nm]		Relative (%)		
Parameter	**Direction**	**Axis**	**MD±SD**	**[95% CI]**	**MD±SD**	**[95% CI]**	**p**
Mean	Positive	||M||	152.0±92.8	[80.6;223.4]	1324.0±808.6	[702.4;1945.5]	0.001
		Mx	5.6±4.4	[2.2;8.9];	56.8±44.9	[22.3;91.3]	0.005
		My	-0.6±8.6	[-7.2;6.0]	-2.5±33.6	[-28.4;23.3]	0.828
		Mz	1.3±3.6	[-1.5;4.1]	15.6±43.7	[-18.0;49.1]	0.317
	Negative	||M||	9.5±10.9	[1.8;17.9]	92.3±105.4	[11.3;173.3]	0.030
		Mx	8.4±8.3	[2.1;14.8]	95.0±93.6	[23.1;166.91]	0.016
		My	3.4±13.5	[-5.7;12.5]	24.4±97.2	[-41.0;90.4]	0.424
		Mz	4.8±7.2	[-0.7;10.3]	53.5±79.7	[-7.8;114.8]	0.079
Variation	Positive	||M||	6.6±13.5	[-2.5;15.7]	37.3±76.8	[-14.2;88.9]	0.138
		Mx	1.3±7.5	[-3.8;6.4]	11.9±68.0	[-33.8;57.5]	0.575
		My	1.1±11.2	[-6.5;8.6]	6.8±72.4	[-41.8;55.5]	0.762
		Mz	-1.1±6.7	[-5.6;3.5]	-12.2±76.7	[-63.7;39.3]	0.610
	Negative	||M||	2.2±9.5	[-4.2;8.6]	17.3±73.7	[-32.2;66.8]	0.453
		Mx	5.3±9.6	[-1.2;11.8]	38.1±69.4	[-8.6;84.7]	0.099
		My	1.1±8.6	[-4.7;6.8]	9.9±79.0	[-43.1;63.0]	0.686
		Mz	2.3±8.4	[-3.3;8.0]	24.3±88.4	[-35.0;83.7]	0.382

Shown are the absolute [Nm] and relative [%] differences between the static tasks and the dynamic tasks through mean (MD), standard deviation (SD), and 95% confidence interval (CI) of these differences for the anterior-posterior (Mx) with lateroflexion to the left (positive) and right (negative), mediolateral (My) with flexion (positive) and extension (negative), longitudinal (Mz) with rotation to the left (positive) and right (negative) axes separately and for the moment magnitude (||M||). Statistically significant differences are marked green.

Table 3.8 | Direction of the net moment around the axis of the static vs dynamic tasks.

			Absolute [Nm]		Relative (%)		
Parameter	**Direction**	**Axis**	**MD±SD**	**[95% CI]**	**MD±SD**	**[95% CI]**	**p**
Mean	Positive	||M||	100.5±132.8	[11.3;189.7]	302.7±399.7	[34.1;571.2]	0.031
		Mx	-6.6±14.8	[-16.6;3.3]	-34.5±76.9	[-86.1;17.1]	0.168
		My	-18.1±25.7	[-35.4;-0.8]	-47.1±66.9	[-92.0;-2.1]	0.042
		Mz	-6.5±8.6	[-12.3;-0.7]	-45.2±60.2	[-85.7;-4.8]	0.032
	Negative	||M||	-44.9±156.2	[-149.9;60.0]	-276.5±960.7	[-921.9;368.9]	0.362
		Mx	-7.7±38.6	[-33.6;18.3]	-54.0±272.6	[-237.1;129.1]	0.526
		My	-22.4±78.0	[-74.8;30.0]	-161.7±561.8	[-539.1;215.7]	0.362
		Mz	-6.7±21.4	[-21.0;7.7]	-59.0±189.5	[-186.3;68.3]	0.326
Variation	Positive	||M||	-6.9±44.9	[-37.1;23.2]	-39.4±254.7	[-210.5;131.7]	0.619
		Mx	-5.1±12.5	[-13.6;3.3]	-46.2±112.8	[-122.0;29.6]	0.204
		My	-4.8±13.1	[-13.6;3.9]	-31.2±84.3	[-87.8;25.4]	0.248
		Mz	-8.0±10.5	[12.1;0.9]	-90.8±10.5	[-171.2;10.4]	0.031
	Negative	||M||	-27.2±97.5	[-92.7;38.3]	-210.5±755.0	[-717.7;296.8]	0.377
		Mx	-1.5±25.3	[-18.5;15.5]	-10.7±182.2	[-133.1;111.7]	0.849
		My	-6.4±26.1	[-23.9;11.1]	-59.0±240.5	[-220.6;102.5]	0.434
		Mz	-3.3±17.6	[-15.1;8.5]	-34.4±183.7	[-157.8;89.1]	0.549

Shown are the absolute [Nm] and relative [%] differences between the static tasks and the dynamic tasks through mean (MD), standard deviation (SD), and 95% confidence interval (CI) of these differences for the anterior-posterior (Mx) with lateroflexion to the left (positive) and right (negative), mediolateral (My) with flexion (positive) and extension (negative), longitudinal (Mz) with rotation to the left (positive) and right (negative) axes separately and for the moment magnitude (||M||).

Table 3.8 summarizes the differences between static and dynamic tasks while taking into account the direction of the movement around the axis. When the direction of the moment around the separated axis was considered, significantly less variation was observed during rotation to the left around the longitudinal axis during dynamic tasks (MD=-90.8±10.5%, p=0.031). In addition, significant differences in the mean moment (||M||, M_y, and M_z) were observed in the positive direction (MD≤302.7±399.7%, p≤0.042).

3.4 | Discussion

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The results of the analysed data showed that the ANN-based method can estimate the net moments of the 6 kg test trials with an accuracy of about 9 Nm in comparison with a LSM-based method after being trained with 0 and 10 kg test trials. These results are in line with the research of Baten, et al. (submitted) and support the notion that the ANN-based method can be used for evaluating lumbar load exposure patterns and exposure levels in real-life work settings. This ANN-based method seemed to be capable of distinguishing differences in the intensity level between light and heavy tasks which are in line with the perceived workload. Also, it can distinguish differences in variation level between static and dynamic tasks. When the direction of the moment around the (anterior-posterior, lateroflexion or longitudinal) axis was considered, similar results were observed between light and heavy tasks. However, between static and dynamics tasks, the variation differences of the net moment were not observed. This is because of the differences due to the direction of the moment around the axis. This indicates that it is important to include the direction of the movement and, thereby, the moment around the axis and (a)symmetrical character of the movement when analysing the lumbar load. It is also important to know in which direction the user is moving, instead of focusing only on the size this moment. This study showed that this system can measure the lumbar load and the direction of this load around the different axes in uncontrolled real-life working conditions.

Like in state-of-the-art research, this study provides insights as provided insight into the usability and validity of this ANN-based method. This method requires only EMG and IMMU data without does require any a priori knowledge on the regarding load for monitoring the lumbar load of physically active workers. Tasks were selected on the basis of actual working activities performed in the natural environments of physically demanding jobs. This study also explored the effect of the direction of the moment around the axis with which asymmetrical working routines can be investigated. For example, in case of a paver who uses only one hand to lift tiles or fabric workers who mainly rotate in one direction or axis. Insight in these movements and moments can provide useful information that can help prevent musculoskeletal complaints might effectively. It should also be mentioned that the diversity in the jobs, related workloads, and selected tasks was a challenging aspect. For example, it was challenging to select uniform tasks for the workers because of the differences in their working activities. Real-life tasks are not merely light, heavy, static, or dynamic; rather, a static or dynamic task may also be light or heavy, which results in an overlap between tasks.

The main weakness of this study is the lack of a reference method during actual work. Currently, the mechanical workload of physically active workers is assessed by observations (video), questionnaires, performance tests, or combinations of motion trackers and force sensors (Jorgensen, et al., 2013; Vieira & Kumar, 2004; Faber, et al., 2015). Both observations and questionnaires are indirect methods and do not provide information about the working posture or related lumbar load. References systems, such as Vicon motion-capture cameras, are not practical or allowed in the real-life working environment (Koopman, et al., 2018; Jorgensen, et al., 2013; Xu, et al., 2012; Juul-Kristensen, et al., 2001). The closest option for a reference method is the method that uses IMMUs and ground reaction forces assessed using an instrumented shoe (Schepers, et al., 2007; Faber, et al., 2018; Koopman, et al., 2018). This method, however, has two major drawbacks. The first drawback is that it yields erroneous results every time an external force other than the ground reaction force is exerted on the lower body (e.g., external forces resulting from supporting loads handled with any part of the lower body or from leaning against a table or workbench). The second drawback is that it requires wearing heavy and somewhat bulky instrumented shoes, which constitutes potential noncompliance with shoe safety functionality and regulations.

The current setup is not usable in real-life physically demanding jobs. Gathering data during actual work seemed to be technically challenging and resulted in the data of 14 out of the 23 subjects not being used in the study analysis. To improve the usability, means an improved data-acquisition setup is required for future studies and applications. This method needs to be validated in follow-up research further with more subjects and in more real-life working situations. Preferably this should be done in work situations in which the instrumented shoes method can serve as a reference and/or situations in which all external forces are known in a way. The environment’s influence on the system (e.g., disturbance in the observability of the earth’s magnetic field) also needs to be further explored (de Vries, et al., 2008) and dealt with. Moreover, the design (mechanical) of the system needs to be improved (e.g., by integrating the sensors in the clothes). In addition, the monitored working posture and lumbar load exposure should be linked to ergonomic guidelines to obtain feedback regarding exceeding acceptable loading levels or loading patterns. This information can be provided to the user (e.g., using a traffic light model) to indicate areas of overload risk. Preferably fully automated with instant feedback to the user. Such a system would provide workers with feedback regarding their working behaviours, which can help them improve their behaviour and decrease their complaints. Both work postures and their net moments as well as the link to ergonomic guidelines need to be further explored in follow-up research. Estimated net moment data seem to be very suitable for exposure variation analysis. Adding load exposure pattern analysis to the current analysis of only the amount of load exposure (Mathiassen and Winkel, 1991), by means of generating a 2D graph of the joint distribution of intensity and of the net moment data dynamically.

The results of this study show that not only can the ANN-based method be used in monitoring lumbar back load exposure in physically demanding jobs, but also it has the potential to be used with office workers (lumbar load during sedentary behaviour) and in the fields of rehabilitation medicine and sports applications.

3.5 | Conclusion

In an in-vivo setup, lumbar loads could be distinguished with the ANN-based method in terms of intensity and variation levels. The moments in the lumbar region are significantly higher during heavy tasks than during light tasks and the amount of variation is significantly higher during dynamic tasks than during static tasks. The estimated net moments were consistent with perceived intensity levels and character of the work task in physically demanding occupations. It was concluded that the results of this study support the validity of this sensor-based system.

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Disclosures

There is no conflict of interest.

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3