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Estimation of the knee joint load using plantar pressure data measured by smart socks: A feasibility study

Pauls Daugulis[a], Aleksejs Kataševs[a,*] and Aleksandrs Okss[b]
[a]*Institute of Biomedical Engineering and Nanotechnologies, Riga Technical University, Riga, Latvia*
[b]*Institute of Design Technologies, Riga Technical University, Riga, Latvia*

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Abstract.
BACKGROUND: Unsupervised sports activities could cause traumas, about 70% of them are those of the low extremities. To avoid traumas, the athlete should be aware of dangerous forces acting within low extremity joints. Research in gait analysis indicated that plantar pressure alteration rate correlates with the gait pace. Thus, the changes in plantar pressure should correlate with the accelerations of extremities, and with the forces, acting in the joints. Smart socks provide a budget solution for the measurement of plantar pressure.
OBJECTIVE: To estimate the correlation between the plantar pressure, measured using smart socks, and forces, acting in the joints of the lower extremities.
METHODS: The research is case study based. The volunteer performed a set of squats. The arbitrary plantar pressure-related data were obtained using originally developed smart socks with embedded knitted pressure sensors. Simultaneously, the lower extremity motion data were recorded using two inertial measurement units, attached to the tight and the ankle, from which the forces acted in the knee joint were estimated. The simplest possible model of knee joint mechanics was used to estimate force.
RESULTS: The estimates of the plantar pressure and knee joint forces demonstrate a strong correlation ($r = 0.75$, $P < 0.001$). The established linear regression equation enables the calculation of the knee joint force with an uncertainty of 22% using the plantar pressure estimate. The accuracy of the classification of the joint force as excessive, i.e., being more than 90% of the maximal force, was 82%.
CONCLUSION: The results demonstrate the feasibility of the smart socks for the estimation of the forces in the knee joints. Smart socks therefore could be used to develop excessive joint force alert devices, that could replace less convenient inertial sensors.

Keywords: Knee joint force, plantar pressure, smart textile, smart socks

1. Introduction

Discussing the positive effect of physical activity on human health, one should always consider potential injuries. Among all sport-related traumas, lower extremity injuries account for 66–73% and are the most widespread [1,2]. From these, knee injuries take 10–25% of all traumas [3]. The damage to the

*Corresponding author: Aleksejs Kataševs, Institute of Biomedical Engineering and Nanotechnologies (BINI), Riga Technical University, Kipsalas Street 6b, LV1048, Riga, Latvia. E-mail: Aleksejs.Katasevs@rtu.lv.

musculoskeletal structures could both lead to acute conditions, such as anterior cruciate ligament rupture or meniscal tears, and provoke degenerative diseases, like joint osteoarthritis or Achilles tendinopathy [4]. The reason for the damage is increased mechanical strain in the muscular and joint tissues, and the resulting disabilities and treatment costs are obvious [4]. The approach used so far to prevent injuries implies various training programs, such as FIFA11+ [5], Knee Control+ [6], HarmoKnee, and many others [7]. The training programs increase athlete muscular strength and tolerance to load, as well as improve body control, stability, and balance, thus reducing the risk of joint tissue overload and related injuries.

The alternative approach implies the estimation of the joint load during the training. This is especially important for amateur sportsmen, as they often are training without supervision by a coach, but is relevant for professional sportsmen, too. With the increase in fatigue, in addition to the reduction in dexterity and accuracy of motion, an athlete loses the "sense of force" [8], hence he or she could not notice overloading. Biomechanical measurements directly demonstrate an increase in such parameters, as knee joint peak flexion and abduction moments, maximum horizontal ground reaction force, valgus moment, etc. [9]. Therefore, the monitoring of the joint forces during training could become a useful tool for prevention of lower limb injuries.

The direct measurement of the joint forces *in vivo* is a highly invasive procedure that requires the insertion of miniaturized force sensors directly in the joint [10] and obviously is not suitable for "in-field" sports applications. The alternative is the calculation of the joint forces on the base of the lower limb biomechanical model [4,11–13]. The input data for the model are obtained using the motion capture technique and include results of kinematic (linear and angular velocities) and dynamic (reaction forces) measurements. The forces of interest are then calculated, using e.g., the inversion dynamic approach [14]. Recently, the machine learning approach was used, too [15]. Hence, there are two prerequisites for the development of joint force monitoring devices: the wearable motion capture technology, which provides kinematic and dynamic data on athlete motion, and the computational model, which enables the calculation of the forces from the measured data. This approach is widely discussed in the literature (see, e.g. [4,16]).

The various design approaches and examples of wearable motion capture systems may be found both in the literature [17–19] and on the market [20,21]. Mostly, such systems are based on inertial measurement units (IMU) and could be equipped with insoles or shoes to measure ground reaction force. IMU-based systems provide accurate data on human limb motion kinematics and dynamics and generally are suitable for the in-field environment.

An important problem with wearable devices is user compliance. Research, made in various fields of wearable use demonstrated a dropout rate of about 20–25% within the first three months and about 50–84% within 1–1.5 years [22,23]. In some short-term studies, dropout rates reached up to 75% within the first two months (see review in [22]). Among factors that influence the user adherence to the device, ease of use, comfort, and unobtrusiveness play an important role [24]. From this point of view, the complexity and cost of advanced IMU-based systems could prevent their routine use, especially by amateur sportsmen. In addition, some full-body IMU suits are often made from synthetic materials and are uncomfortable causing excessive sweating.

To summarize, there is a need for a cost-effective and simple solution to monitor limb joint forces in sports exercises. A possible approach is the use of so-called "smart socks", i.e., socks, equipped with plantar pressure measurement sensors and data acquisition system. Various models of such socks are both commercially available [25] and described in the literature [26–29]. The reason to use plantar pressure measuring socks as a tool for the estimation of joint forces is a relationship between plantar pressure and different kinematic motion parameters, such as knee flexion angles [30], foot joint flexion angles [31], gait cadence [32] and speed [33]. An association between running speed and plantar pressure distribution pattern was reported, as well [34]. At a higher walking speed, there are faster changes in both the limb motion velocity and plantar pressure. As the change in velocity over unit time is, in fact, acceleration, one could hypothesize that the changes in plantar pressure should correlate with the limb accelerations and, therefore, with dynamic forces acting on the joints. At the same time, it cannot be ruled out that there could be a correlation between joint forces and other parameters of plantar pressure signal waveform (amplitude, time parameters, etc.).

The objective of the present preliminary research is to evaluate the feasibility of the proposed hypothesis. The research is limited to the case study of the correlation between the forces acting on the knee joint and parameters of the plantar pressure waveforms, measured using smart socks with integrated stress sensors.

2. Materials and methods

2.1. Smart socks and data acquisition module

The research used dAid smart socks and data acquisition modules, developed at Riga Technical University [29,35]. The socks (Fig. 1a) have six knitted resistive sensors, positioned on the foot plantar surface when the socks are on (Fig. 2b). The sensors and conductive traces are knitted using conductive yarn and integrated into the sock directly during the manufacturing process. The conductivity of the sensors increases with applied pressure. The traces are connected to the originally designed data acquisition module (Fig. 1c) using the snap button-ended wires. The data acquisition module enables simultaneous connection of 8 resistive sensors (although only 6 of them were used). Sensor resistance is measured using the calibrated current injection method. The resulting voltage drop is converted using 10-bit ADC and converted to resistance; the resistance measurement range could be adjusted from 2 kOhms up to 1024 kOhms. Alongside this, the module is equipped with an embedded 6D IMU, that enables the measurement of linear and angular acceleration. The module data acquisition rate is about 160 s^{-1}/channel. The module communicates acquired data via Bluetooth®-2.1 channel. Each data packet contains the time mark (module internal time in milliseconds), components of module acceleration (A_x, A_y, A_z), measured in units of g, components of a quaternion (Q_w, Q_x, Q_y, Q_z), measured in the range $[-1; +1]$, and eight measured in kiloohms sensor resistances $R_1 - R_8$. The receiver is a laptop with Windows-based custom-made data acquisition software, enabling recording of the acceleration, quaternion component, and sensor resistance waveforms as well as real-time display of the acquired signals. The module enables measurements of acceleration up to 32 g, and resistances up to 1024 kΩ. The rechargeable battery of the module enables 8-hours of continuous operation.

The experimental setup included a smart sock and two data acquisition modules (Fig. 2). Within the scope of the present paper, measurements were made on the subject's left leg only. The first module was attached to the lateral surface of the subject's ankle at the distance d_1 from the bottom edge of the module to the ground (Fig. 2a), 10 cm above the lateral malleolus. This module was connected to the sock for plantar pressure measurements. The second accelerometer was connected to the lateral surface of the subject's tight 10 cm above the superior edge of the patella at the distance d_2 from the ground (Fig. 2b). In both cases, the modules were fastened using adhesive tape. Modules were positioned with IMU x-axis directed forward and y-axis directed downward. All measurements started from the same pre-defined starting position (Fig. 2c), straight posture with both feet shoulder-width apart. Each data recording began with a few seconds of rest, followed by exercise.

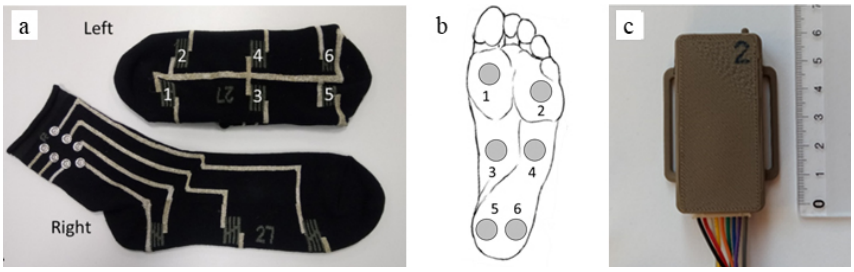

Fig. 1. Pair of dAid smart socks with knitted sensors marked by numbers (a); typical position of sensors over the foot plantar surface (b); data acquisition module (c).

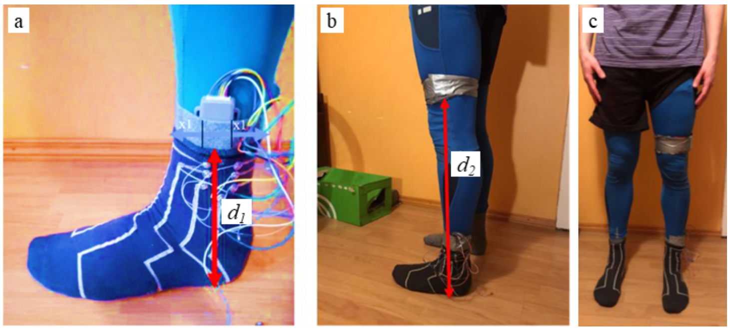

Fig. 2. Experimental setup: Position of the ankle (a) and tight (b) modules, initial position for measurements (c).

The modules did not have a synchronization option. To synchronize the tight and ankle modules, a sharp stomp was made at the beginning of each data recording. Then the acceleration waveforms, recorded by each module were used to check the synchronization of the modules and upon necessity align the waveforms manually, using the stomp-related spike as an alignment landmark. The inaccuracy of alignment was within one data point or 6 ms.

The recorded waveforms were digitally filtered using 2nd order Butterworth filter with a cut-off frequency 6 Hz for the squat exercises and 15 Hz for walking/running exercises. Such filters are often used in IMU applications [36,37].

2.2. *The exercise*

The research was conducted, involving only one volunteer subject – one of the authors of the research. The subject got into the starting position, then performed a series of 10 squats. The subject was instructed to perform squats as naturally as possible, trying to perform them at a similar depth, as well as perform squats steadily, without rapid acceleration. The exercise was performed barefoot. The series was repeated three times. In parallel to the data recording, all measurements were recorded on video – this visual information facilitated the process of result analysis.

2.3. *The biomechanical model and calculation of moments and forces*

The present study is limited to the analysis of motion in the plane, which coincides with the x-y plane of IMU. Any motion in the lateral, or z-axis direction, as well as rotation of tight and calf around their longitudinal axes, are ignored. All exercises were designed in a manner that the subject moved only

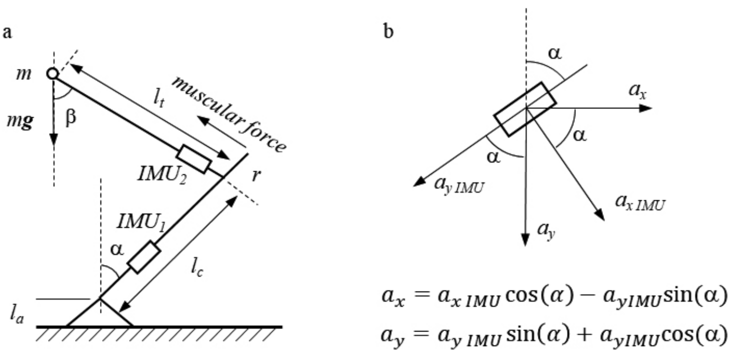

Fig. 3. Geometry of the leg model for the squat exercise (a); the relation between IMU and global coordinate systems (b). The segments of the leg are the height of the ankle l_a, length of the calf l_c, and length of the tight l_t. The loading mass is concentrated in point m.

along a straight line, with the movement of each segment being tracked along the x-y plane. For the squat motion, the tight and calf were considered as being coplanar all squat time. Figure 3a presents the geometry of the lower limb, where the height of the ankle l_a was measured from the ground to the lateral malleolus, the length of the calf l_c was measured from the lateral malleolus to the lateral femoral condyle, and the length of the tight l_t was measured from the lateral femoral condyle to the greater trochanter.

The angular position of the calf and tight were described by declination from the plumb line, measured by the angles α and β. In the starting position, both angles were taken equal to zero. Angles were calculated from the quaternion data: the Euler's yaw angle was calculated first, the angles α and β were calculated as a difference between the current yaw angle and the angle, calculated for the starting position. The angles were used further to recalculate the acceleration vector from the IMU-related coordinate system to the global coordinate system (Fig. 3b).

The calculation of forces was made using the model (Fig. 3a), based on the simplified inverse dynamic approach [14]. As the subject made squats slowly, the tight was considered as being in quasi-equilibrium. The loading mass m, being $1/2$ of the total body mass, was concentrated at the proximal end of the tight. In such a setup, the torque of the gravity force $N_g = mgl_t \cdot \sin\beta$ is equal to the torque, provided by quadriceps muscular force $N_m = F_m r$, where the lever arm r is the distance between the knee rotation axis and the quadriceps tendon attachment point. In this work, the arm r was taken equal to $1/2$ of the subject knee joint anterior-posterior thickness, or 4.5 cm. The force F, applied to the knee joint, was evaluated as being equal to the quadriceps muscle force:

$$F = \frac{mgl_t \sin\beta}{r}. \quad (1)$$

Using this model, the knee torque and force were calculated for all squat duration.

The parameters of the subject, involved in the research were: body mass 86 kg, the height of the ankle $l_a = 11$ cm, the length of the calf $l_c = 41$ cm, and the length of the tight $l_t = 44$ cm.

2.4. The plantar pressure estimation

In the scope of the present research, the plantar pressure was not calculated. Instead, the values of reciprocal readouts of the sock sensors were used. These reciprocal values, measured in kOhm^{-1}, are directly proportional to the plantar pressure. Such an approach is adequate, and even preferable, for the purpose of future application of the smart socks for the development of knee joint overload application:

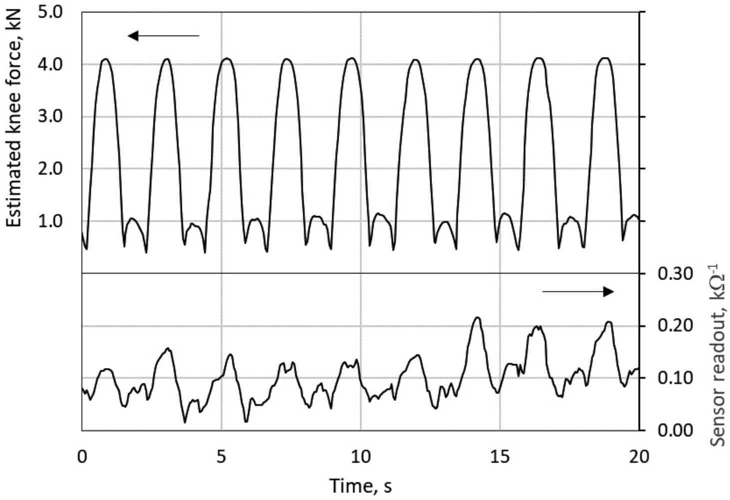

Fig. 4. The typical waveforms of the estimated knee joint force (top) and average reciprocal sock sensors readout (bottom) for a series of squats.

exploring the relationship between knee joint load and reciprocal sensor readout, one could use the latter as an input value for the alert algorithm directly, without additional recalculation from sock data to the plantar pressure data.

The research used data from metatarsal sensors, middle sensor, and heel sensors (sensors 1, 2, 4, 5, 6, Fig. 1a). Sensor 3, placed under the foot ark, was excluded, as it was not loaded during barefoot exercises. The sum of the reciprocal readouts from all five sensors was used to detect foot contact instances in walking/running tasks and separate stance phase waveforms.

3. Results

3.1. Correlation between knee joint force and sock sensor data

Figure 4 represents the typical waveforms of the estimated knee joint forces and reciprocal sock sensor readouts in a series of squats. The calculated knee joint force ranged from about 0.5 kN at the beginning of the squat (i.e. in the start position) to 4 kN at the maximal squat depth. These values correspond to the range of 0.58 to 4.6 body weights (BW) and, generally are close to data, reported in the literature for squatting [10] and high-risk dynamic tasks [38], and are reasonably higher, than forces, reported for walking/running [15]. The force maximums generally coincided with the sensor readouts, and hence, with plantar pressure maximums. The readout, presented in Fig. 4. is an average of five sensors waveforms. Analysis of the recordings of each individual sensor revealed that not all sensor waveforms exhibit clear congruence with the force waveform, as the averaged data do. The best coincidence was found for the lateral toe sensor (sensor 2, Fig. 1b). The coincidence between waveforms was evaluated both graphically and numerically. Figure 5 shows correlation diagrams between knee joint force and readouts of some sensors. The diagrams reveal a moderate knee joint force association with averaged sensors data and data from the lateral toe sensor (sensor 2), but poor correlation with, e.g., medial and heel sensors (sensors 4 and 6). The correlation coefficients, summarized in Table 1, endorse this observation. These (Pearson) correlation coefficients were calculated for each sensor and for each squat series. The

Table 1
Correlation coefficients between estimated knee joint force and reciprocal sensor readouts for three 10-squat series. For all coefficients, the P-value is < 0.001

Sensor	Measurement series		
	1 set	2 set	3 set
1	0.55	0.45	0.47
2	0.74	0.74	0.79
4	0.17	0.52	0.25
5	0.55	0.67	0.59
6	−0.65	−0.68	−0.63
Average	0.75	0.75	0.80

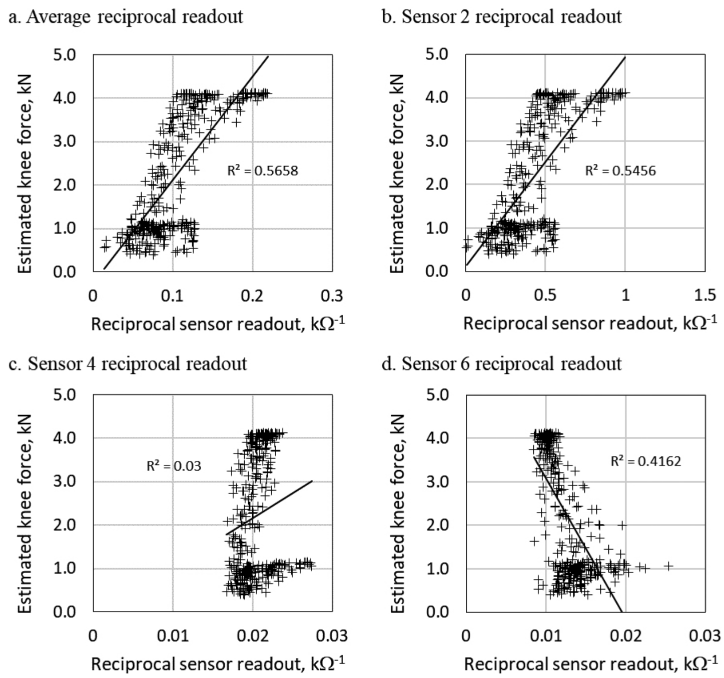

Fig. 5. The correlation diagram for the estimated knee joint force and reciprocal data of the selected sensors: a) averaged data; b) toe lateral sensor (Sensor 2); c) middle lateral sensor (Sensor 4); d) heel lateral sensor (Sensor 6).

P-value, associated with the t-test was lower than 0.001 for each coefficient. This indicates a high level of significance, but such low P-values may be related just to the big number of points (more than 3000 for each measurement). A strong correlation with correlation coefficients exceeding 0.7 is observed for the lateral toe sensor and averaged data only. Note that for the heel sensor, the correlation coefficient is negative, and its value, being about -0.65, suggests a moderate correlation. This result, generally, could be expected, as it just indicates the lift of the heel during deep squats. As the averaged sensor data provided the highest correlation coefficients, these data were used for further analysis.

3.2. Linear regression model

A simple mathematical model for the prediction of knee joint force was built using linear regression.

Table 2
Linear regression coefficients for the estimation of the knee joint force

Measurement series	A model with $b \neq 0$			A model with $b = 0$	
	$a\pm$ SD, kN·kΩ	$b\pm$ SD, kN	R^2	$a\pm$ SD, kN·kΩ	R^2
Series 1	23.8 ± 1.1	-0.26 ± 0.13	0.57	21.7 ± 0.4	0.88
Series 2	21.3 ± 1.0	-0.26 ± 0.13	0.56	19.4 ± 0.4	0.87
Series 3	23.8 ± 0.8	-0.66 ± 0.10	0.72	19.1 ± 0.3	0.91
All data	21.9 ± 0.57	-0.33 ± 0.07	0.57	19.5 ± 0.2	0.88

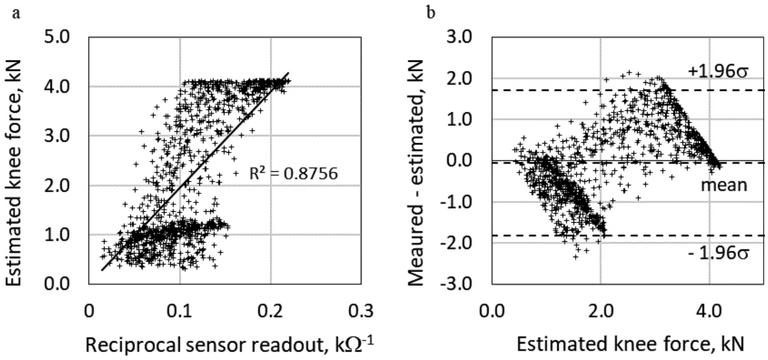

Fig. 6. Linear regression approximation for the estimated knee joint force (a) and corresponding Bland-Altman plot (b).

Two models were considered: one with non-zero intercept, and another with zero intercept. The model was constructed for each squat series separately and for the merged together data from all series. Table 2 summarizes the parameters of the models. For all models, either with zero or non-zero intercept, the model coefficients are significant at the level of 0.05: the $\pm$ 1.96σ confidence intervals do not include zero. On the other hand, the R^2 values are greater for the models with zero intercept (0.87–0.91), as compared with models with non-zero intercept (0.56–0.72). In addition, the $\pm$ 1.96σ confidence intervals of both slopes and intercepts are overlapping for different measurement series. Taking the above into account, the predictive model was built using all series data, with zero intercept. The resulting model is:

$$F[kN] = 19.5X[k\Omega^{-1}], \tag{2}$$

where F is a knee joint force, but X is an average of the reciprocals of readouts of the sock sensors, measured in kOhms. In this model, the slope coefficient is determined with an uncertainty of 1.1%. The standard deviation of the force estimate is 0.9 kN, that, considering the range of the estimated force from 0.5 to 4 kN, corresponds to the fiducial uncertainty 22%.

Figure 6a shows the linear model in comparison with the scattering diagram knee joint force – sensor readouts. Despite the rather high R^2 value, the experimental data demonstrates a high degree of variability. To compare the model prediction with the experimental data, the Bland-Altman plot was constructed (Fig. 6b). The plot shows rather poor agreement between the model and experiment. The uncertainty of the force estimation could reach 2 kN in the middle of the knee force variation range. Still, for the forces that fall in the interval from about 0.9 from maximal force and above, the uncertainty remains within 20%. Since the potential application of the model is a prediction of extremely high forces and overloads, such accuracy at the highest force values could be satisfactory.

Table 3
Contingency table for the excessive force test

Observed knee force	Predicted knee force $\leqslant 0.9\ F_{\max}$	Predicted knee force $> 0.9\ F_{\max}$	Total
$\leqslant 0.9\ F_{\max}$	829	0	829
$> 0.9\ F_{\max}$	200	90	290
Total	1029	90	1119

3.3. The overload detection

To simulate the detection of the extremely high forces, the developed linear model (Eq. (2)) was used to design an overload test. The force equal to the 0.9 of the maximal observed force 4.1 kN was chosen as a threshold. If the force, calculated from Eq. (2), exceeded the threshold, the test was considered as positive – overload was detected. The prediction of the linear model was compared with actual knee joint force values, classified using the same principle. The 2x2 contingency table of the test is presented in Table 3. The resulting parameters of the tests are sensitivity 0.31, and specificity 1.00. The total accuracy of the test, measured as the ratio of the total number of correct predictions (either positive or negative) to the total number of cases, was 0.82. Such parameters mean that the test could detect about 31% of all overload cases, but never generates false alert. Bearing in mind the nature of physical exercises that are repeated for a long time, such a low sensitivity still is acceptable. As the potential purpose of the perspective alert system is to prevent long-term overload, even with low sensitivity, the athlete will be sooner or later alerted about excessive training. For instance, during running, the alert comes at each third step, on average.

4. Discussion

The obvious limitation of the presented study is the use of the two-dimensional model of lower extremity. Generally, two-dimensional models provide lower accuracy as compared with three-dimensional ones [13], alongside, use of two-dimensional models excludes from consideration such intrinsically three-dimensional movements as cutting maneuvers, typical for sport games.

Despite of this limitation, the obtained characteristics of the relationship between estimated knee joint forces and reciprocal sensors readouts X are compatible with those obtained in other studies for the relationship between estimated joint forces and other kinematic or dynamic measurands. For instance, [14] reported determination coefficient between instrumentally measured peak knee flexion moments and medial knee joint contact forces within 0.75–0.93 range, that is close to one, obtained in the present study (0.87–0.91). Another study [15] evaluated the correlation coefficient between accelerometry – based and optical motion-capture based estimation of the knee joint forces for various running, walking, and jumping modes within 0.60–0.94, that is compatible with the correlation coefficients of 0.75–0.80, obtained in the present study (Table 1). Similar values of correlation coefficients were observed in [30] for the knee flection angles and metatarsal ground reaction forces ($|r| \sim 0.72$) and in [31] for plantar pressure and ankle flection angles ($r = 0.73$–0.84). This consideration illustrates that, for the estimation of the relationship between knee joint forces and plantar pressure, the smart socks are as accurate as other alternative methods, used so far to establish association between various kinematic or dynamic lower extremities' motion characteristics.

The obtained pilot results indicated some potential of the smart socks systems as a possible tool for the estimation of joint forces and development of the sportsmen overload detection applications, as there is a strong correlation between the readouts of the socks sensors and forces, acted in the limb joints. The attractiveness of this approach is in a great extent related to the cost-effectiveness of the knitted smart socks, that could make them available to the broad community of amateur sportsmen. Unfortunately, the present pilot case study demonstrated rather poor force prediction accuracy. The way to increase the prediction value of the system could be related to the use of neural network for the sock data analysis. This approach was already described in the literature [37]. On the other hand, application of the neural network requires remarkable computational power, that could complicate the design of the device. Therefore, other methods of data processing should be tested in future.

Another important limitation of the present work is its case study nature. The research was based on one subject only, performing one type of exercise. To estimate the feasibility of the proposed approach in a greater scope, the involvement of more subjects and widening of the exercise area is of critical importance. The most attractive is to test the socks system ability to predict overload during walking and running.

5. Conclusion

The present paper demonstrated limited feasibility of the smart sock system for the estimation of the forces in the knee joint. Despite low force prediction accuracy, the proposed smart socks can detect excessive knee joint forces, and hereby could be used for the development of the excessive joint force alert device, that could replace less convenient inertial sensors.

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Conflict of interest

None to report.

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