

RESEARCH ARTICLE

Open Access



A pilot study on locomotion training via biomechanical models and a wearable haptic feedback system

Emel Demircan* 

Abstract

Locomotion is a fundamental human skill. Real-time sensing and feedback is a promising strategy for motion training to reconstruct healthy locomotion patterns lost due to aging or disease, and to prevent injuries. In this paper, we present a pilot study on locomotion training via biomechanical modeling and a wearable haptic feedback system. In addition, a novel simulation framework for motion tracking and analysis is introduced. This unified framework, implemented within the Unity environment, is used to analyze subject's baseline and performance characteristics, and to provide real-time haptic feedback during locomotion. The framework incorporates accurate musculoskeletal models derived from OpenSim, closed-form calculations of muscle routing kinematics and kinematic Jacobian matrices, dynamic performance metrics (i.e., muscular effort), human motion reconstruction via inertial measurement unit (IMU) sensors, and real-time visualization of the motion and its dynamics. A pilot study was conducted in which 6 healthy subjects learned to alter running patterns to lower the knee flexion moment (KFM) through haptic feedback. We targeted three gait parameters (trunk lean, cadence, and foot strike) that previous studies had identified as having an influence on reducing the knee flexion moment and associated with increased risk of running injuries. All subjects were able to adopt altered running patterns requiring simultaneous changes to these kinematic parameters and reduced their KFM to 30–85% of their baseline values. The muscular effort during motion training stayed comparable to subjects' baseline. This study shows that biomechanical modeling, together with real-time sensing and wearable haptic feedback can greatly increase the efficiency of motion training.

Keywords: Locomotion, Haptic feedback, Knee flexion moment, Rehabilitation robotics, Wearables

Introduction

Despite the positive health effects, there is a high incidence of lower extremity injuries during running [1, 2]. Although estimates suggest that 10–20% of Americans run regularly, with 40–50% of these injured annually [3], causation is more complex, with a survey of results across 17 published studies, involving a range specific population characteristics (age, experience, gender, etc.) showing annual injury rates can vary from 19 to 79% [4].

Among these injuries, half occur at the knee joint, with patellofemoral pain (PFP) being the most common diagnosis [2, 4]. PFP can lead to severe pain and disability and is a precursor of knee osteoarthritis [5].

Joint moments can be used as an indicator of joint loading and have potential application for sports performance and injury prevention. Peak knee flexion moment and flexion moment impulse are related to the progression of patellofemoral joint (PFJ) osteoarthritis [6]. Increased knee flexion moment is suggestive of greater quadriceps force requirements and has been reported to result in higher PFJ reaction force and stress [7, 8].

Real-time feedback is a promising strategy for motion retraining. Visual or tactile feedback have been

*Correspondence: emel.demircan@csulb.edu

Department of Mechanical and Aerospace Engineering, Department of Biomedical Engineering, California State University Long Beach, 1250 Bellflower Blvd, Long Beach 90840, USA

implemented to alter knee and impact loading [9–13]. The use of vibrotactile feedback in several medical and non-medical areas has been established [14]. Individualized data-driven models were used to train novel gaits involving a combination of kinematic modifications [15]. In a comparative study by [16], haptic feedback combined with visual feedback yielded better task learning performance for the lower extremity, compared to visual feedback or haptic feedback alone. A more recent review by [17] documented that studies focused on the clinical applications of wearable feedback for human gait often used haptic and auditory feedback sensations. Both visual-auditory feedback and visual-tactile feedback provide advantages in reducing reaction times and improving performance [18]. Visual-tactile feedback is more effective when multiple tasks are performed and cognitive workload conditions are high [18]. In a study that evaluated assistive navigation systems for the blind, auditory feedback resulted in a 22 times higher cognitive load than haptic feedback [19]. Previous studies have observed that vision feedback provides a high degree of precision [12]. Vibration provides simple and intuitive feedback, particularly when vision is otherwise occupied [15]. In addition, vibration conveys Cartesian space directional cues well.

Haptic feedback is increasingly becoming an essential component for maximizing the effectiveness of the interaction between the human user and a machine. Using touch to communicate with users, haptic feedback provides a relative sensation that is important in daily exploration tasks. It can also be a means of delivering cues to a user learning new motor skills [20] or for patients undergoing rehabilitation therapy [21]. As haptic systems are being developed as wearable devices, this technology is finding a surge of applications in healthcare, virtual reality, remote assistance, and robotics [22]. Some common examples of haptic feedback in everyday life includes the vibration alerts in a modern smart watch or the resistance given to the driver by the car's electric power steering system. There are many different types of haptic feedback modalities that are used for different tasks and applications. This paper explores the different modalities used and discusses the use of vibrotactile feedback during locomotion.

During skin stretch, the surface of the haptic device imparts a shear force on the user's skin to excite its mechanoreceptors. By stretching the skin tangentially, skin-stretch feedback can give directional information to the user [23]. A study by Norman et al. demonstrates the effectiveness of a simple fingerpad skin stretch device to guide a user's arm via haptic cues and real-time corrective feedback [24]. With the motivation to increase embodiment between amputees and their prosthetic

device, Battaglia et al. evaluated the ability of a rotational skin-stretch haptic wearable to convey proprioceptive information of a robotic hand [25]. For lower limb amputees, Husman et al. proposes the use of a lateral skin-stretch haptic wearable to cue the user of gait events during ambulation [26].

During electrotactile feedback, electric signals stimulate nerves in the skin via surface electrodes. The main benefit of this modality is that there are no moving parts and it can deliver a variety of different sensations compared to other forms of feedback [27]. An experiment by Pamungkas et al. describes an electrotactile feedback system that conveys surface properties of a remote object to the back of the user's hand [28]. Using amplitude modulated electrotactile feedback to the neck, Arakeri et al. developed a system that provides information regarding the grip force and closure of a hand grasping an object [29].

Vibrotactile feedback is perhaps one of the most commonly recognized types of haptic feedback as it is found in mobile phones and gaming console controllers. Vibrotactile actuators become ideal in many haptic applications due to its low cost, small size, and its ability to be effective when placed at almost anywhere on the body [30]. When combined with motion capture technology, vibrotactile feedback can be used to help students learn a new motor skill such as playing the violin [20]. More notably, vibrotactile feedback systems are researched in areas that would help improve gait performance for the elderly that suffer from the risk of falling or patients that experience a functional disability after stroke. A study by Lee et al. demonstrates the efficacy of vibrotactile cueing to prevent falls using a split-belt treadmill to simulate unpredictable perturbations [31]. A portable gait asymmetry rehabilitation system by Azfal et al. delivers vibrotactile cues based on gait phase measurement to improve gait symmetry for individuals with stroke [21, 32]. Two studies demonstrated that haptic feedback can be used to identify and retrain gait parameters such as toe-in/toe-out configuration and stride length during walking [33, 34]. A separate study have shown positive results among patients who require gait guidance and suffer from gait abnormality due to lack of balance for rehabilitation [35].

Researchers proposed using multiple haptic modalities in their device to provide multimodal sensory feedback. Alonzo et al. proposed stacking vibrotactile stimulators on top of electrotactile stimulators to make the system more compact [36]. Another wearable haptic device could deliver skin-stretch, pressure, and vibrotactile to convey information about the status of the teleoperated robot and it has been shown to effectively improve the user operation performance [37]. Skin stretch is a natural sensing mode for proprioception, thus making it ideal to

intuitively convey proprioceptive information to the user [25], even when compared to vibrotactile feedback [38]. As an alert scheme, vibrotactile feedback was found to be superior to electrotactile feedback in terms of accuracy and user comfort [39]. Vibrotactile feedback systems have also been shown to be an effective and non-invasive method to convey information or cues that is safer than electro- and thermal feedback [40].

Computer simulations with accurate musculoskeletal models can provide detailed insights into the biomechanics of walking [41] and running [42] during treatments. In the biomechanics community, highly accurate human models of lower and upper extremities taken from cadaveric specimens have been used to investigate muscle coordination to identify sources of pathological movement and to establish a scientific basis for treatment planning and design [43, 44]. Several studies have utilized biomechanical modeling and dynamic simulations of the musculoskeletal system to identify the contributors to an individual gait [45–53]. Metabolic cost models have also been introduced for the improvement of robotic assistance that considered passive dynamics [54] and fully actuated systems for human walking [55–58]. OpenSim [59] is a widely used biomechanical modeling and analysis application that introduced several innovations in: joint modeling [60], multi-body and contact modeling, and numerical methods [61] to the biomechanics community. It provides biologically accurate joint and muscle models that can be used to create anatomically accurate musculoskeletal systems. However, since OpenSim utilizes numerical methods to estimate motion dynamics, it cannot be used to simultaneously track and analyze the dynamics of motion in real-time.

There exists a plethora of simulation software that can be used to model and analyze multi-body systems, some of which are commercially available, while others are in open source. Current software systems that can be used to build and analyze human and animal models include: LifeModeler (commercial) [62], AnyBody (commercial) [63], Visual3D (commercial) [64], SIMM [43], D-Flow (commercial) [65, 66], V-REP (commercial) [67], and OpenSim [59] (open source). AnyBody, Visual3D, and D-Flow are only capable of inverse dynamics. Other software systems can be used for forward dynamics, but they require pre-calculated muscle activations, thus limiting their use for predicting patient response to medical interventions [68]. OpenSim, Anybody, LifeModeler, and SIMM lack live dynamic simulation capabilities; they cannot be used to simultaneously track and analyze motion in real-time. D-Flow, Visual3D, and V-Rep, although capable of live simulations, are not open source. Moreover, simulation development within these software systems is often cumbersome, and interfacing with

third-party systems (i.e. VR equipment, IMUs, haptic systems) is not straightforward for the average developer. Developing a simulation framework within a widely supported engine, such as Unity or Unreal Engine, would be much more practical because the resulting products can be designed to be scalable, highly customizable, easy-to-use, and open source.

Despite all the recent advances in biomechanics, robotics, and computer animation research, there is no established scientific understanding of how real-time multi-modal feedback integrates into locomotion training to improve motor learning and performance [14]. In addition, vibrotactile stimulation as a feedback tool in sports has not been supported by scientific evidence [14]. Finally, there is no unified and portable framework that integrates real-time sensing and feedback with human biomechanical models.

In this paper, we present a pilot study on locomotion training via a wearable haptic feedback system and the use of biomechanical modeling. This provides us with preliminary results to understand the effect of real-time vibrotactile feedback to elicit motor adaptation in locomotion. This work builds upon our recent results on human perception accuracy of vibrotactile feedback during locomotion [69]. In addition, a novel simulation framework for motion tracking and analysis is introduced. This unified framework, implemented within the Unity environment, is used to analyze a subject's baseline and performance characteristics, and to provide real-time haptic feedback during locomotion. A notable advantage of building the framework within the Unity environment is that the user has access to Unity's extensive Asset Store [70], which contains a plethora of assets that the user can integrate with the simulation framework when building custom motion analysis applications. The framework incorporates accurate musculoskeletal models derived from OpenSim, closed-form calculations of muscle routing kinematics and kinematic Jacobian matrices, dynamic performance metrics (i.e., muscular effort) [71], human motion reconstruction via IMU sensors, and real-time visualization of the motion and its dynamics.

Methods

The following sections present the aim, design, and setting of the study, including the description of the simulation software, motion reconstruction and analysis methods, subjects and subject preparation, the experimental protocol, the haptic feedback system, and the type of statistical analysis used.

Software

The simulation framework was developed specifically to interpret and build OpenSim models within Unity.

The framework implements OpenSim's musculoskeletal definitions and incorporates many of OpenSim's unique behaviors, such as: conditional muscle path points, moving muscle path points, cubic spline joint connectivity, and coordinate coupling constraints. The framework was also designed to be used within Unity's editor window in order to give the user the ability to load and customize dynamic models while in edit mode. The framework provides matrix operations and symbolic calculus functionality via interprocess communication with MIT's Math.NET Symbolics [72], the C++ Mathematical Expression Toolkit Library (ExprTk) [73], and the ALGLIB numerical analysis and data-processing library [74]. The interface with Math.NET Symbolics provides the user with the ability to symbolically calculate the kinematic and muscular Jacobians of a multi-body model during runtime. The output of the symbolic calculation is a symbolic expression that can be interpreted using ExprTk. However, symbolic interpretation is computationally expensive, especially for large expressions (i.e. kinematic Jacobian). In order to circumvent this problem, we added dynamic compilation capabilities to the framework that enables the user to compile symbolic expressions during runtime and save the output assemblies to disk for future instances. This runtime-compilation, in combination with the closed-form symbolic computation provided by Math.NET Symbolics, is the reason why the framework is able to perform complex dynamic computations at a simulation frame rate of 100 FPS or higher while simultaneously tracking motion (using 6 core Intel(R) Core(TM) i7-8700K CPU @ 3.70GHz, 32GB of RAM, and a Nvidia GeForce GTX 1080Ti graphics card with 27 GB of GPU memory.). The framework provides a generic motion tracking interface by implementing the motion decomposition algorithms from [75–77] to decompose the transform of a body into the generalized coordinates of a multi-body model. This motion tracking interface is independent of the motion-capture system used and solely relies on the motion of the body that is being tracked; this enables the user to use the framework with pre-constructed humanoid models, which often come with the Unity packages of motion-capture systems. The Unity environment provides a framework with the ability to be interfaced with Unity-compatible, third-party systems, such as the Oculus Rift [78] and the abovementioned IMU system. Moreover, the Unity API can be used alongside the simulation framework to create intuitive and easily customizable user interfaces that provide the user with the ability to interact with the loaded multi-body models. Figure 1 shows the simulation framework within the Unity environment with real-time motion reconstruction using the Perception Neuron Pro IMU motion-capture system [79].

Muscle Jacobian and effort implementation

The ForceSet element of the OpenSim format contains the definitions of the forces in the model. The OpenSim format supports various types of forces, such as external point forces and spring generalized forces [19, 20]. However, within our framework, only the muscle path actuator type has been implemented. The muscle path actuator type refers to a force-generating element that applies controllable tension along a defined geometry path. The force-generating behavior of this actuator type is defined by the muscle definitions that derive from it. Each of these muscle definitions contains a unique definition that describes the muscle's force-generating behavior. These unique definitions are, however, out of the scope of our framework since the full implementation of the listed muscle types is currently not part of the framework's requirements.

At the current state of our framework, the only elements that are actively utilized are the "MaxIsometricForce" and "GeometryPath" elements. The "MaxIsometricForce" element is used for the muscle effort calculations. The "GeometryPath" element contains the path points that the muscle actuator must follow sequentially in every simulation frame as well as the properties that pertain to the visualization of the muscle element. Within the framework, the "GeometryPath" element contains the definitions for the muscle actuator's "PathPointSet" elements that contain the definitions of each path point that outlines the geometric path of the muscle actuator. In accordance to the adopted OpenSim format, all the path point types must contain definitions for the path point's "location" and "body" elements. The "location" element contains three numerical entries which refer to the XYZ location (or starting location) of the path point with respect to the reference frame of the defined "body" element. The ConditionalPathPoint and MovingPathPoint types contain additional elements that must be defined in order to represent their unique behaviors.

As it pertains to a multibody musculoskeletal model, the muscle Jacobian represents the muscle moment arm, which is a measure of the effectiveness of a muscle's contractual force in generating torque about a given joint [80]. The Jacobian of a muscle can be calculated by taking the partial derivatives of the muscle's total length with respect to the system's independent generalized coordinates. For a multi-body system with muscle actuators, the muscle Jacobian of each muscle can be vertically concatenated to represent the system's muscle Jacobian matrix. The muscle Jacobian matrix can then be used to relate the muscle forces to the muscle-induced joint torques along the system's generalized coordinates by using the relationship introduced in [80]. Within our framework, all

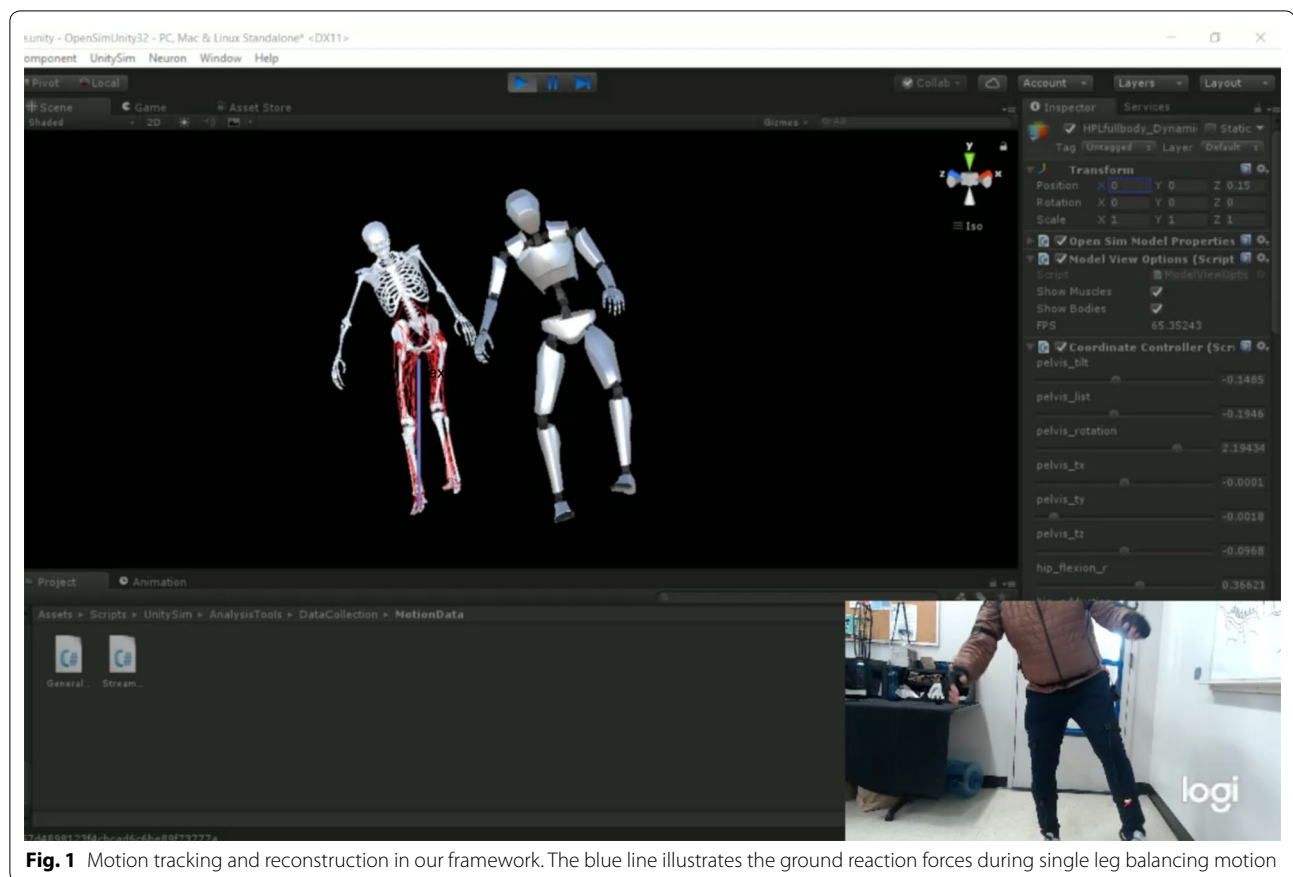


Fig. 1 Motion tracking and reconstruction in our framework. The blue line illustrates the ground reaction forces during single leg balancing motion

point-to-point muscle connections are linear; there are no curved muscle paths. In fact, for muscle wrapping, the framework uses point-to-point connections between moving path points and conditional path points to emulate a curved path. The framework also assumes that the length of a muscle is purely kinematic and depends only on the configuration. It also assumes that the muscle routing kinematics always take the shortest muscle path under a given set of muscle via points. Finally, the muscular effort criterion is implemented as introduced in [80] using the generalized operational space forces for a given task and the biomechanical advantage function [71]. The joint space equation of motion for an open-chain multi-body system is implemented in the framework. Modeling the centrifugal and Coriolis terms is computationally expensive, especially for large multi-body systems. For this reason, the Coriolis and centrifugal terms are currently not implemented within the framework. The gravity, mass matrix, and generalized coordinate derivative terms are, on the other hand, implemented.

Motion tracking and reconstruction

Within our framework, a generic interface was implemented [81] by developing a motion-tracking element

that decomposes the transform of any referenced object into the generalized coordinate values required to actuate the imitating “Joint” or “Body” element towards the transform of the referenced object. The referenced object can be a hierarchy of objects. In this case, the transform that the motion-tracking element will try to decompose is the transform of the last element in the object hierarchy with respect to the frame of the root object. The motion-tracking element is characterized as generic because it does not depend on the type of motion capture system that is being used; it depends solely on the transform of the object that it is tracking. This characteristic is valuable because most motion capture system companies that provide interfaces between their devices and Unity also provide a rigged humanoid model that can simply be dragged and dropped into the Unity environment and work with the motion capture system out of the box. The limbs of the humanoid model can then be assigned to the appropriate motion-tracking elements, which in turn follow the translation and orientation of the assigned limbs without being directly connected to the motion capture system. Within our framework, the generic motion-tracking element is represented by the JointTracker class. The transform decomposition is achieved by extracting

the translational and rotational components of a referenced object's transform and then projecting those components onto the generalized coordinates of the body that is trying to imitate the referenced object's transform.

In order to evaluate the performance of the JointTracker element, Perception Neuron full-body IMU suit was integrated into the framework. As expected, Noitom already provides the software (Axis Neuron) and the rigged humanoid model required to use the IMU motion capture system within Unity. As designed, the only task that must be completed to use the IMU motion capture system with our framework is to connect the individual limbs of the humanoid model to the appropriate JointTracker elements. The ground reaction forces are estimated by our framework using the motion data from IMU and the subject-specific mass matrix. Both the kinematic and kinetic values estimated by our framework were validated against the data reported in the literature [6].

Haptic feedback system

We used miniature soft-mounted (i.e., vibrotactile) actuators [82–84] to ensure light haptic devices did not impede the natural motions of the human body where they are mounted. The vibration signals were generated as follows: (1) “continuous” vibration (500 ms) and (2) five “discrete” pulses (100 ms) [85]. The feedback patterns were randomly spaced out by 5 s, 10 s, and 15 s. The torso feedback was in the form of continuous vibrations on the upper back or staggered vibrations on the lower back. The subject was instructed to lean forward while they experience continuous vibrations on the upper back and lean back when they experienced staggered vibrations on the lower back while they were running. The knee feedback was in the form of continuous or staggered vibrations on the lateral knee joints. The subject was instructed to increase cadence when they experienced continuous vibrations and reduce cadence when they experienced staggered vibrations while they were running. The ankle feedback was in the form of continuous or staggered vibrations on the lateral ankle joints. The subject was instructed to increase foot-drop angle when they experienced continuous vibrations and reduce foot-drop angle when they experienced staggered vibrations while they were running. The technical specifications of the haptic feedback system and vibration types were introduced in our recent study [69].

Experiments

Subjects and subject preparation

Eight healthy subjects (4 male, 4 female; avg. age: 25.375 years, range: 20–39 years; avg. BMI: 22.912 kg/m², range: 19.1–27.4 kg/m²) participated after giving informed

consent in accordance with the California State University Long Beach Institutional Review Board. Eight subjects were sufficient for identifying a knee flexion moment reduction based on a priori sample size calculations. To have scientifically correct subject-specific scaling for the modeling purposes in our future work, we did not include children or the elderly. Inclusion criteria for subject recruitment are the following: (1) between ages of 18 and 40 years old; (2) familiar with running on a treadmill; and (3) run at least 8 miles/week for 4 weeks prior to participation. Exclusion criteria for subject recruitment are the following: (1) history of lower extremity or low back surgery that may affect running kinematics, kinetics or muscle activation; (2) lower extremity or low back pathology that causes pain or discomfort during the experiment or within 3 months prior to participation; and (3) any physical or mental condition that may prevent the subject from running safely.

Each subject was prepared with a lycra-based athletic compression suit. The suit included vibrotactile motors that provided haptic feedback on six locations. The locations of the vibrotactile motors included the upper back, lower back, lateral knee joint (both knees), and lateral ankle joint (both ankles). In addition to the compression suit, the subject also wore a Perception Neuron Pro IMU full-body suit over the compression suit. 17 sensors placed on each subject were used to track the whole-body motion. The location of the sensors are included in the following list: head, upper back, shoulders (left and right), upper arms (left and right), forearms (left and right), hands (left and right), lower Back (waist), upper legs (left and right), lower legs (left and right), feet (left and right). Experimental set up took approximately 15 min. Figure 2 shows the subject wearing the sensing and feedback system.

Motion training

The objective of the experiment was to adjust the subject's posture while running with haptic feedback. We targeted three gait parameters that previous studies had identified as having an influence on reducing the knee flexion moment: trunk lean [8], cadence [86, 87], and foot strike [88, 89]. Each of these kinematic variable has been shown to associate with increased risk of running injuries. As specified in [15], data was collected/sampled every 25 steps, as this was a sufficient number of steps to modify a single motion parameter.

The experiment consisted of three major parts. The first major part of the experiment collected the subject's baseline information from a 90-s running session. The subject then took a 2 min break before moving on to the second major part of the experiment to avoid fatigue. The second major part of the experiment was the first haptic



Fig. 2 Subject wearing the wireless sensing and feedback system

feedback session that consisted of three 120-s runs with 2 min breaks in between each run. The subject experienced 1 of 3 types of haptic feedback during each run of the first feedback session. These vibrations guided the subject to adjust specific kinematic variables during the run. The three types of haptic feedback included the following: torso feedback (increase/decrease trunk lean), knee feedback (increase/decrease cadence), and ankle feedback (increase/decrease foot drop angle). The second major part of the experiment was the second haptic feedback session that consisted of four 120-s runs with 2 min breaks in between. The subject experienced combinations of 2 types haptic feedback as follows: torso and knees (increase/decrease trunk lean and increase/decrease cadence), torso and ankles (increase/decrease trunk lean and increase/decrease foot drop angle), and knees and ankles (increase/decrease cadence and increase/decrease foot drop angle) during each run of the second feedback session. Vibrations were sent in either continuous or staggered mode [69] to indicate the subject

must increase or decrease the kinematic variable of interest. The subject was asked to try to maintain a posture and pace that resulted in no haptic feedback for a total of 15 s. The subject ran a maximum of 15.5 min throughout the experiment. However, this time can be less depending on the subject's success of meeting the posture and pace goal. Immediately after the experiment, subjects were also asked to report the comfort level during locomotion using bipolar Likert-type ten-point scales.

Data analysis

The motion data was acquired using Perception Neuron Pro suit at 120 Hz sampling rate. The musculoskeletal model was scaled to each subject's total mass and height. The ground reaction forces and the angles in the lower limb joints were determined throughout the entire stance phase using our simulation framework. Kinematic parameters including trunk lean angle, cadence, foot drop angle, and running speed were determined for the baseline and haptic training. The net internal ankle, knee, and hip joint moments in the sagittal and frontal planes were calculated using a Newton-Euler inverse dynamics technique implemented in our simulation framework. All net joint moments were normalized to subject's baseline. In addition, the average peak values of KFM during stance phase of running were determined. The whole-body effort was calculated using the algorithm presented in the previous sections. Figure 3 shows the motion reconstruction using a scaled human biomechanical model in our framework. An example of subject's baseline data is also shown in Fig. 3.

Statistical analysis

To evaluate statistical differences in the results of the experiment, analyses of variance ANOVAs were performed. Repeated measures ANOVAs were performed to compare the results within subjects. When significant main effects were identified, paired t-tests were used to compare cases. Correlation coefficients were calculated to determine if the percent reduction in KFM was correlated with the effort or the baseline KFM. Alpha was set at 0.05 for all statistical analyses.

Results and discussion

Results

All 8 subjects responded to the haptic feedback devices by running with the new patterns, and reduced their KFM with haptic feedback compared with baseline. The new running patterns resulted in increases in trunk lean angle, foot drop angle, and cadence, and they resulted in a decrease in KFM. The final KFM was significantly lower than baseline in all cases $p < 0.01$. The computed effort remained comparable to subject's baseline.

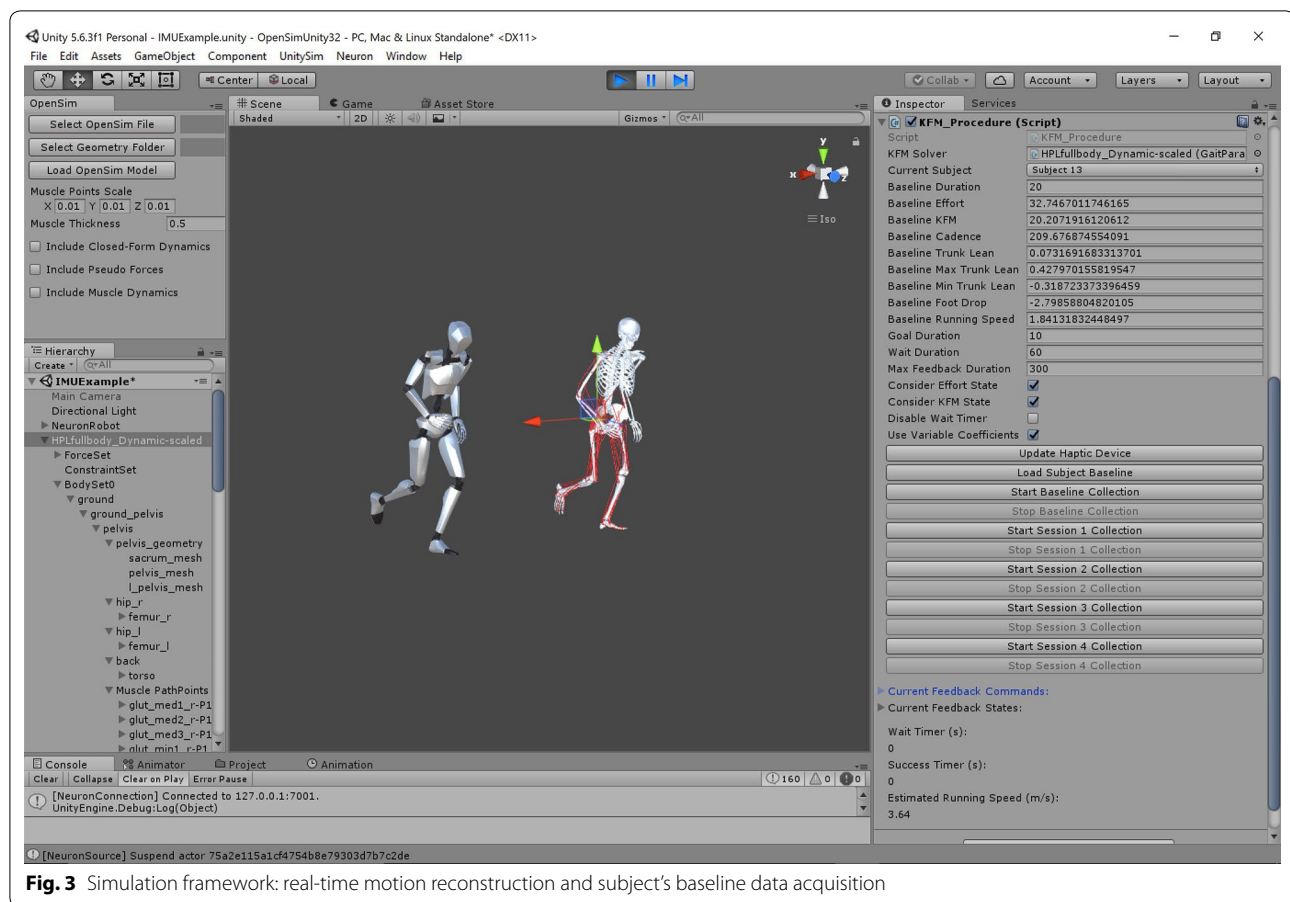


Fig. 3 Simulation framework: real-time motion reconstruction and subject's baseline data acquisition

Table 1 Sample subject's baseline generated by the framework

	subject's baseline	generated
Effort		21.47
Cadence (steps/min)		155.22
Trunk lean (deg)		0.04
Max. trunk lean (deg)		0.48
Min. trunk lean (deg)		− 0.33
Foot drop (deg)		5.68
Speed (m/s)		2.19

Post-experiment bipolar Likert-type surveys indicated an average comfort level of 8.5 in ten-point scales. A typical example of subject's baseline generated by the framework is shown in Table 1. Figure 4 shows the post-training KFM values as a percentage of the subjects' baseline.

Tables 2 and 3 show average speed, best feedback type, average peak KFM, and average effort for each subject. The magnitude of reduction in the KFM varied from 14.78% to more than 80%. The average peak of the KFM was significantly lower in the post-training case ($p < 0.01$). The average KFM reduction was

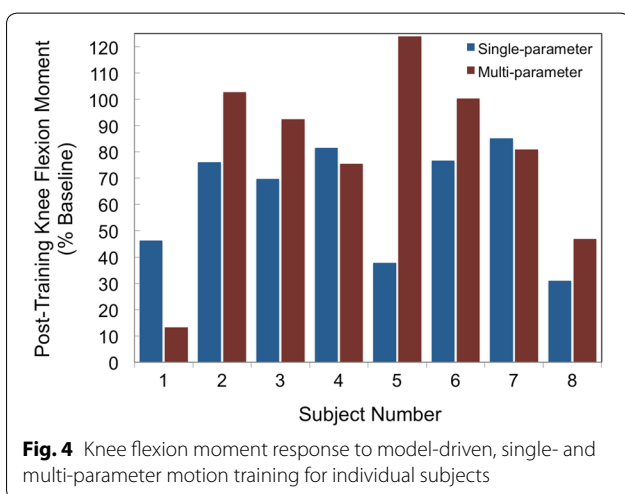


Fig. 4 Knee flexion moment response to model-driven, single- and multi-parameter motion training for individual subjects

41.27% for male and 32.61% for female subjects. There was a significant positive correlation between the single-parameter feedback post-training percent KFM values and the effort ($r = 0.64$). Similarly, there was a significant positive correlation between the multi-parameter

Table 2 Results for all subjects by single feedback type

Subject	Gender	Avg. speed (m/s)	Best feedback type	Avg. KFM (% Baseline)	Avg. effort (% Baseline)
1	m	1.89	Foot drop	46.38	114.39
2	m	2.19	Trunk lean	75.99	176.31
3	f	1.49	Trunk lean	69.71	88.93
4	m	1.83	Trunk lean	81.58	113.25
5	f	1.56	Foot drop	37.92	114.19
6	f	2.14	Foot drop	76.73	99.98
7	f	1.51	Cadence	85.22	107.53
8	m	1.84	Trunk lean	30.97	34.56
All				63.06 (21.28)	106.14 (38.85)
P-Value				$p < 0.001$	

KFM is the average value of the peak knee flexion moments during the training. Moments are scaled by subject's baseline. The final KFM was significantly lower than baseline in all cases $p < 0.01$. The effort remained comparable to subject's baseline

Table 3 Results for all subjects by multiple feedback type

Subject number	Gender	Avg. speed (m/s)	Best feedback type	Avg. KFM (% Baseline)	Avg. effort (% Baseline)
1	m	1.89	Foot drop + trunk lean	13.37	44.68
2	m	2.19	Foot drop + trunk lean	102.80	167.11
3	f	1.49	Foot drop + trunk lean	92.39	101.76
4	m	1.83	Trunk lean + cadence	75.41	121.14
5	f	1.56	Foot drop + cadence	123.96	127.99
6	f	2.14	Foot drop + cadence	100.37	83.47
7	f	1.51	Foot drop + cadence	80.91	57.27
8	m	1.84	Foot drop + trunk lean	47.03	35.53
All				79.53 (34.98)	92.37 (45.64)
P-Value				$p < 0.001$	

KFM is the average value of the peak knee flexion moments during the training. Moments are scaled by subject's baseline. The final KFM was significantly lower than baseline in all cases $p < 0.01$. The effort remained comparable to subject's baseline

feedback post-training percent KFM values and the effort ($r = 0.72$). No statistical difference was found between single- and multi-parameter feedback. Post-training running patterns evidenced increases in kinematic variables (trunk lean, foot drop, and cadence) as shown in Table 4 ($p < 0.05$ for all variables).

Discussion

This pilot study showed that providing real-time feedback based on biomechanical modeling and haptics was an efficient locomotion training method for reducing the KFM. This real-time feedback approach for a repetitive task has the potential to greatly improve the effectiveness of subject-specific motion training and reduce the risk of injuries. Our study conforms to previous studies that identified the kinematic variables as having an influence on reducing the knee flexion moment: trunk lean [8], cadence [86, 87], and foot strike [88, 89]. Increasing trunk lean, cadence and foot drop angle decreased the

KFM during stance, which aligns with the previous work. In addition, the results of our pilot study showed the combined effect of the kinematic variables on KFM via a fully-portable feedback system. Although the direction of change for each running kinematic variable was generally consistent across subjects, the amount of change varied considerably. This was due to subject-specific differences in degree of influence of running parameters on the KFM.

The best feedback type for each subject is shown in Tables 2 and 3. Baseline and trained running kinematics were shown in Table 4. In single-parameter training, the foot drop angle (i.e., forefoot strike) had a significant impact on the KFM (average KFM reduction: 46.33%, $p < 0.01$). Additionally, increased trunk lean and cadence caused reductions in the average peak of the KFM. The average reduction in KFM was 35.43%, 46.33%, and 14.78% with single-parameter trunk lean, foot drop, and cadence feedback, respectively. In multi-parameter

Table 4 Baseline and trained running kinematics for all subjects

Subject	Trunk lean (deg)			Foot drop (deg)			Cadence (steps/min)		
	Baseline	New	Change	Baseline	New	Change	Baseline	New	Change
1	0.12	4.17	4.04	− 4.10	13.06	17.17	169.52	180.23	10.71
2	0.03	12.35	12.31	5.68	6.38	0.70	154.98	169.79	14.81
3	− 0.15	12.09	12.25	6.51	16.71	10.19	156.76	161.2	4.44
4	− 0.02	10.93	10.96	9.96	6.76	− 3.20	152.75	159.23	6.48
5	0.05	2.93	2.87	− 1.58	− 11.12	− 9.54	175.06	158.47	− 16.59
6	0.22	21.70	21.48	11.79	5.37	− 6.42	172.55	181.08	8.53
7	− 0.03	− 1.38	− 1.34	− 3.01	8.91	11.93	167.26	172.81	5.55
8	0.07	− 3.00	− 3.07	− 2.79	7.36	10.16	172.31	175.43	3.12
All	0.03 (0.11)	7.47 (8.27)	7.43 (8.25)	2.80 (6.39)	6.68 (8.15)	3.87 (9.76)	165.14 (8.90)	169.78 (9.18)	4.63 (9.35)
P-Value	$p < 0.05$			$p < 0.05$			$p < 0.05$		

The optimal KFM state kinematics highlight the subject-specific nature of the motion training

training, the combination of trunk lean and foot drop angles had a significant impact on KFM (average KFM reduction: 36.09%, $p < 0.01$). The second most effective multi-parameter training was the combination of trunk lean angle and cadence, which decreased the average KFM by 24.58%. The combination of foot drop angle and cadence didn't have significant effect on the KFM. Overall, the computed effort remained comparable to subject's baseline. This finding evidenced that the new running patterns did not significantly increase muscle efforts, and thus remained comfortable to the subject.

In summary, this study showed that biomechanical modeling with haptic feedback is an effective method for improving posture for efficient running patterns. Significant KFM reductions were evidenced in every individual due to the subject-specific variations and without altering subject's effort. Novel running patterns were identified and adopted in multiple training sessions using a model-based, portable sensing and feedback system. In the future, we plan to extend our framework and experiments to include multimodal cues and assess the retention of the adopted motion patterns. Plans for multi-modal feedback include to provide both concurrent and terminal feedback for running. A retention test will be implemented while subjects walk without any feedback. Terminal feedback has been found to promote motor learning and facilitates motor retention [90]. In addition to visual feedback, participants of the study will receive tactile feedback. To verify and validate the types of feedback, a between-participant design will investigate participants' abilities to detect the feedback. In the tactile condition, participants will receive a vibratory stimulus and self-select a running speed for a duration of 15 min. The timing and location of the feedback while running will be determined by a 'priority' schedule used by [85].

Participants will be asked to respond to the feedback by indicating to experimenters they felt the vibration or repeat the body part that was provided by the auditory feedback.

Conclusions

Since the 1970s, running popularity has continuously grown as a professional and recreational sport. It is estimated 65 million people participated in this activity in United States alone in 2017 [91]. Between 1990 and 2013, road race finishers grew from five millions to over 19 million [92]. Contributing to its popularity, running was proved to have major health benefits, such as improving cardiovascular endurance and overall quality of life, and decreasing the prevalence of Type 2 diabetes, obesity, and hypertension [93]. In the U.S., 10–20% of the population run regularly, with 40–50% of those injured annually [3]. Among these injuries, half occur at the knee joint, with patellofemoral pain (PFP) being the most common diagnosis [2, 4]. PFP can lead to severe pain and disability and is a precursor of knee osteoarthritis [5]. There lies a huge potential for sports science and physical therapy to use feedback mechanisms as intervention tool [14]. One of the advantages of motion feedback is the enhancement of a user's ability to function in a cognitively overloaded situation, such as a multi-task scenario (e.g., running while adapting to postural changes for one or more segments). Our framework is unique in that it integrates portable sensors, models motion dynamics in real-time, and provides concurrent feedback to improve running.

A limitation in this study was that motion training was performed on healthy subjects without prior injury. To have scientifically correct subject-specific modeling and scaling for our biomechanical model in this study, we did not include patients or the elderly, although this can be

extended in future work. History of lower extremity or low back surgery may affect running kinematics, kinetics or muscle activation. Similarly, lower extremity or low back pathology may cause pain or discomfort during running. Older patients may also have difficulty remembering gait modifications trained with real-time feedback, particularly if the new gait patterns were a complicated combination of movement alterations. Other future work includes the integration of a multi-modal feedback mechanism in the framework, as subject's perception of feedback modalities may vary based on the age, gender, fitness level, and injury history.

This pilot study demonstrated the feasibility of providing real-time haptic feedback for motion training using a fully portable, model-based framework. While the proposed framework and pilot study address improving running kinematics and associated health outcomes, future studies should be associated with utilizing the framework with modified models for use with activities of daily living (ADL) and sport activities. Improved performance of ADLs will assist with elderly populations in fall reduction and disabled communities with impaired sensory systems. With the rapid increase in repetitive sport injuries, use of our framework with sport specific modeling procedures and learning protocols may provide mechanisms to analyze and improve kinematics and kinetics for the purposes of injury reduction and improved performance.

Acknowledgements

We thank colleagues E. Recinos, I. Khoo, H. Teng, and W. Wu for assistance in the collection of motion data and for comments on versions of this manuscript.

Authors' contributions

ED designed the study and collection, analyzed and interpreted the data, and wrote the manuscript. The author read and approved the final manuscript.

Funding

The design of the study and collection, analysis, and interpretation of data were funded by California State University Long Beach Faculty Seed Grants.

Availability of data and materials

The data analysed during the current study are not publicly available due to individual privacy, but are available from the corresponding author on reasonable request.

Competing interests

The author declares that she has no competing interests.

Author's information

ED is an Assistant Professor at the Departments of Mechanical and Aerospace Engineering and Biomedical Engineering at California State University, Long Beach. ED obtained her Ph.D in Mechanical Engineering from Stanford University in 2012. She was a postdoctoral scholar at Stanford from 2012 to 2014 and a visiting assistant professor at the University of Tokyo from 2014 to 2015. She was also a part-time scientist at Lucile Salter Packard Children's Hospital Gait Analysis Lab at Stanford University. ED's research focuses on the application of dynamics and control theory for the simulation and analysis of biomechanical and robotic systems. Her research interests include cyber-physical systems, rehabilitation robotics, sports biomechanics, natural motion generation in humanoid robotics, and human motion synthesis. ED is an OpenSim Fellow; and the founder/co-chair of the IEEE RAS Technical Committee on "Human

Movement Understanding." She is actively collaborating with clinical, athletic, and industrial partners; and she is involved in professional and educational activities within the IEEE Robotics Society.

Received: 29 December 2019 Accepted: 26 March 2020

Published online: 07 April 2020

References

- Koplan JP, Rothenberg R, Jones E (1995) The natural history of exercise: a 10-yr follow-up of a cohort of runners. *Med Sci Sports Exerc* 27(8):1180–1184
- Taunton JE, Ryan MB, Clement DB, McKenzie DC, Lloyd-Smith DR, Zumbo BD (2002) A retrospective case-control analysis of 2002 running injuries. *Br J Sports Med* 36(2):95–101
- Fields KB, Sykes JC, Walker KM, Jackson JC (2010) Prevention of running injuries. *Curr Sports Med Rep* 9:176–182
- van Gent RN, Siem D, van Middelkoop M, van Os AG, Bierma-Zeinstra SMA, Koes BW, Taunton JE (2007) Incidence and determinants of lower extremity running injuries in long distance runners: a systematic review. *Br J Sports Med* 41(8):469–480
- Thomas MJ, Wood L, Selfe J, Peat G (2010) Anterior knee pain in younger adults as a precursor to subsequent patellofemoral osteoarthritis: a systematic review. *BMC Musculoskelet Disord* 11(1):201
- Teng H-L, MacLeod TD, Link TM, Majumdar S, Souza RB (2015) Higher knee flexion moment during the second half of the stance phase of gait is associated with the progression of osteoarthritis of the patellofemoral joint on magnetic resonance imaging. *J Orthopaed Sports Phys Therapy* 45(9):656–664
- Ho K, Blanchette M, Powers CM (2012) The influence of heel height on patellofemoral joint kinetics during walking. *Curr Sports Med Rep* 35:271–275
- Teng H-L, CM P (2014) Sagittal plane trunk posture influences patellofemoral joint stress during running. *J Orthop Sports Phys Ther* 44(10):785–792
- Barrios JA, Crossley KM, Davis IS (2012) Gait retraining to reduce the knee adduction moment through real-time visual feedback of dynamic knee alignment. *J Biomech Eng* 43(11):2208–2213. <https://doi.org/10.1016/j.jbiomech.2010.03.040>
- Riskowski JL, Mikesky AE, Bahamonde RE, Burr DB (2009) Design and validation of a knee brace with feedback to reduce the rate of loading. *J Biomech Eng*. <https://doi.org/10.1115/1.3148858>
- Dowling AV, Fisher DS, Andriacchi TP (2009) Gait modification via verbal instruction and an active feedback system to reduce peak knee adduction moment. *J Biomech TP Eng*. <https://doi.org/10.1115/1.4001584>
- Wheeler JW, Shull PB, Besier TF (2011) Real-time knee adduction moment feedback for gait retraining through visual and tactile displays. *J Biomech Eng*. <https://doi.org/10.1115/1.4003621>
- Crowell HP, Milner CE, Hamill J, Davis IS (2010) Reducing impact loading during running with the use of real-time visual feedback. *J Orth Sports Phys Ther* 40(4):206–213
- VanBreda E, Verwulgen S, Saeys W, Wuyts K, Peeters T (2017) Vibrotactile feedback as a tool to improve motor learning and sports performance: a systematic review. *BMJ Open Sport Exerc Med* 3:21–53
- Shull PB, Lurie KL, Cutkosky MR, Besier TF (2011) Training multi-parameter gaits to reduce the knee adduction moment with data-driven models and haptic feedback. *J Biomech Eng*. 44(8):1605–1609. <https://doi.org/10.1016/j.jbiomech.2011.03.016>
- Koritnik T, Koenig A, Bajd T, Riener R, Munih M (2010) Comparison of visual and haptic feedback during training of lower extremities. *Gait Posture* 32(4):540–546. <https://doi.org/10.1016/j.gaitpost.2010.07.017>
- Shull PB, Jirattigalachote W, Hunt MA, Cutkosky MR, Delp SL (2014) Quantified self and human movement: a review on the clinical impact of wearable sensing and feedback for gait analysis and intervention. *Gait Posture* 40(1):11–19. <https://doi.org/10.1016/j.gaitpost.2014.03.189>
- Burke JL, Prewett MS, Gray AA, Yang L, Stilson FRB, Covert MD, Elliot LR, Redden E (2006) Comparing the effects of visual-auditory and visual-tactile feedback on user performance: a meta-analysis. In: *Proc. of the 8th International Conference on Multimodal Interfaces*, Canada, pp 108–117

19. Martinez M, Constantinescu A, Schuete B, Koester D, Steiffelbogen R (2014) Cognitive evaluation of haptic and audio feedback in short range navigation tasks. In: Proc. of the International Conference on Computers for Handicapped Persons, ICCHP, pp 128–135
20. Van Der Linden J, Schoonderwaldt E, Bird J, Johnson R (2011) Music-Jacket - combining motion capture and vibrotactile feedback to teach violin bowing. *IEEE Transact Instrum Meas* 60(1):104–113. <https://doi.org/10.1109/TIM.2010.2065770>
21. Afzal MR, Lee H, Yoon J, Oh MK, Lee CH (2017) Development of an augmented feedback system for training of gait improvement using vibrotactile cues. 2017 14th International Conference on Ubiquitous Robots and Ambient Intelligence, URAI 2017, 818–823. <https://doi.org/10.1109/URAI.2017.7992833>
22. Pacchierotti C, Sinclair S, Solazzi M, Frisoli A, Hayward V, Prattichizzo D (2017) Wearable haptic systems for the fingertip and the hand: taxonomy, review, and perspectives. *IEEE Transactions on Haptics* 10(4):580–600. <https://doi.org/10.1109/TOH.2017.2689006>
23. Chinello F, Pacchierotti C, Tsagarakis NG, Prattichizzo D (2016) Design of a wearable skin stretch cutaneous device for the upper limb. *IEEE Haptics Symposium, HAPTICS 2016-April(April)*, 14–20. <https://doi.org/10.1109/HAPTICS.2016.7463149>
24. Norman SL, Doxon AJ, Gleeson BT, Provancher WR (2014) Planar hand motion guidance using fingertip skin-stretch feedback. *IEEE Transactions on Haptics* 7(2):121–130. <https://doi.org/10.1109/TOH.2013.2296306>
25. Battaglia E, Clark JP, Bianchi M, Catalano MG, Bicchi A, O'malley MK (2019) Skin stretch haptic feedback to convey closure information in anthropomorphic, under-actuated upper limb soft prostheses. *IEEE Transact Haptics* 12(4):508–520. <https://doi.org/10.1109/TOH.2019.2915075>
26. Husman MAB, Magbool HF, Awad MI, Abouhossein A, Dehghani-Sanij AA (2016) A wearable skin stretch haptic feedback device: Towards improving balance control in lower limb amputees. *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS 2016-October*, 2120–2123. <https://doi.org/10.1109/EMBC.2016.7591147>
27. Pamungkas DS, Caesarendra W (2018) Overview electro-tactile feedback for enhancing human computer interface. *J Phys*. <https://doi.org/10.1088/1742-6596/1007/1/012001>
28. Pamungkas D, Ward K (2015) Tactile sensing system using electro-tactile feedback. *ICARA 2015 - Proceedings of the 2015 6th International Conference on Automation, Robotics and Applications*, 295–299. <https://doi.org/10.1109/ICARA.2015.7081163>
29. Arakeri TJ, Hasse BA, Fuglevand AJ (2018) Object discrimination using electro-tactile feedback. *J Neural Eng*. <https://doi.org/10.1088/1741-2552/aabc9a>
30. Bark K, Hyman E, Tan F, Cha E, Jax SA, Buxbaum LJ, Kuchenbecker KJ (2015) Effects of Vibrotactile Feedback on Human Learning of Arm Motions (V) 1–42. <https://doi.org/10.1109/TNSRE.2014.2327229.Effects>
31. Lee BC, Martin BJ, Thrasher TA, Layne CS (2017) The effect of vibrotactile cuing on recovery strategies from a treadmill-induced trip. *IEEE Trans Neural Syst Rehab Eng* 25(3):235–243. <https://doi.org/10.1109/TNSRE.2016.2556690>
32. Afzal MR, Lee H-S, Oh M-K, Lee J-H, Yoon J (2014) Effects of vibrotactile feedback on human learning of arm motions. *BioMed Res Int* 2015:1–4
33. Xu J, Lee UH, Bao T, Huang Y, Sienko KH, Shull PB (2017) Wearable sensing and haptic feedback research platform for gait retraining. 2017 IEEE 14th International Conference on Wearable and Implantable Body Sensor Networks, BSN 2017, 125–128. <https://doi.org/10.1109/BSN.2017.7936023>
34. Saichi K, Yasuda K, Kitaji Y, Kaibuki N, Iwata H (2016) Development and pilot clinical evaluation of a haptic-based perception-empathy biofeedback device for gait rehabilitation. *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS 2016-October*, 6158–6161. <https://doi.org/10.1109/EMBC.2016.7592134>
35. Park MH, Kim DW (2015) The Development of Gait Detection and Vibration Stimulus System. *Proceedings - International Conference on Intelligent Systems, Modelling and Simulation, ISMS 2015-October*, 93–95. <https://doi.org/10.1109/ISMS.2015.28>
36. Alonzo MD, Dosen S, Cipriani C, Member S, Farina D (2014) HyVE-hybrid vibro-electrotactile stimulation—is an efficient approach to multi-channel sensory feedback. *IEEE Trans Haptics*. 7(2):181–190
37. Aggravi M, Pause F, Giordano PR, Pacchierotti C (2018) Design and evaluation of a wearable haptic device for skin stretch, pressure, and vibrotactile stimuli. *IEEE Robot Autom Lett* 3(3):2166–2173. <https://doi.org/10.1109/LRA.2018.2810887>
38. Bark K, Wheeler JW, Premakumar S, Cutkosky MR (2008) Comparison of skin stretch and vibrotactile stimulation for feedback of proprioceptive information. *Symposium on Haptics Interfaces for Virtual Environment and Teleoperator Systems 2008 - Proceedings, Haptics*, 71–78. <https://doi.org/10.1109/HAPTICS.2008.4479916>
39. Ng G, Barralon P, Dumont G, Schwarz SKW, Ansermino JM (2007) Optimizing the Tactile Display of Physiological Information : Vibro-Tactile vs. Electro-Tactile Stimulation, and Forearm or Wrist Location, 4202–4205
40. Alahakone AU, Senanayake SMNA (2009) Vibrotactile feedback systems: Current trends in rehabilitation, sports and information display. *IEEE/ASME International Conference on Advanced Intelligent Mechatronics, AIM*, 1148–1153. <https://doi.org/10.1109/AIM.2009.5229741>
41. Liu MQ, Anderson FC, Schwartz MH, Delp SL (2008) Muscle contributions to support and progression over a range of walking speeds. *J Biomech* 41(15):3243–3252. <https://doi.org/10.1016/j.jbiomech.2008.07.031>
42. Hamner SR, Seth A, Delp SL (2010) Muscle contributions to propulsion and support during running. *J Biomech* 43(14):2709–2716. <https://doi.org/10.1016/j.jbiomech.2010.06.025>
43. Delp SL, Loan PJ, Hoy MG, Zajac FE, Topp EL, Rosen JM (1990) An interactive graphics-based model of the lower extremity to study orthopaedic surgical procedures. *IEEE Trans Biomed Eng* 37:757–767
44. Holzbaur KRC, Murray WM, Delp SL (2005) A model of the upper extremity for simulating musculoskeletal surgery and analyzing neuromuscular control. *Ann Biomed Eng* 33:829–840
45. Zajac FE, Neptune RR, Kautz SA (2003) Biomechanics and muscle coordination of human walking: Part II: Lessons from dynamical simulations and clinical implications. *Gait Posture*. [https://doi.org/10.1016/S0966-6362\(02\)00069-3](https://doi.org/10.1016/S0966-6362(02)00069-3)
46. Cenciariini M, Dollar AM (2011) Biomechanical considerations in the design of lower limb exoskeletons. *IEEE Int Conf Rehab Robot*. <https://doi.org/10.1109/ICORR.2011.5975366>
47. Liu MQ, Anderson FC, Pandy MG, Delp SL (2006) Muscles that support the body also modulate forward progression during walking. *J Biomech* 39(14):2623–2630. <https://doi.org/10.1016/j.jbiomech.2005.08.017>
48. John CT, Seth A, Schwartz MH, Delp SL (2012) Contributions of muscles to mediolateral ground reaction force over a range of walking speeds. *J Biomech* 45(14):2438–2443. <https://doi.org/10.1016/j.jbiomech.2012.06.037>
49. Kuo AD (2007) The six determinants of gait and the inverted pendulum analogy: a dynamic walking perspective. *Human Mov Sci* 26(4):617–656. <https://doi.org/10.1016/j.humov.2007.04.003>
50. Arnold AS, Schwartz MH, Thelen DG, Delp SL (2007) Contributions of muscles to terminal-swing knee motions vary with walking speed. *J Biomech* 40(16):3660–3671. <https://doi.org/10.1016/j.jbiomech.2007.06.006>
51. Anderson FC, Goldberg SR, Pandy MG, Delp SL (2004) Contributions of muscle forces and toe-off kinematics to peak knee flexion during the swing phase of normal gait: An induced position analysis. *J Biomech* 37(5):731–737. <https://doi.org/10.1016/j.jbiomech.2003.09.018>
52. Arnold AS, Anderson FC, Pandy MG, Delp SL (2005) Muscular contributions to hip and knee extension during the single limb stance phase of normal gait: a framework for investigating the causes of crouch gait. *J Biomech* 38(11):2181–2189. <https://doi.org/10.1016/j.jbiomech.2004.09.036>
53. Barrett RS, Besier TF, Lloyd DG (2007) Individual muscle contributions to the swing phase of gait: an EMG-based forward dynamics modelling approach. *Simul Model Pract Theory* 15(9):1146–1155. <https://doi.org/10.1016/j.simpat.2007.07.005>
54. Walsh CJ (2006) Biomimetic design of an under-actuated leg exoskeleton for load-carrying augmentation. Thesis (S.M.)—Massachusetts Institute of Technology, Department of Mechanical Engineering
55. Ackermann M, Schiehlen W (2006) Dynamic analysis of human gait disorder and metabolic cost estimation. *Arch Appl Mech* 75(10–12):569–594. <https://doi.org/10.1007/s00419-006-0027-7>
56. Bregman DJJ, Van der Krogt MM, de Groot V, Harlaar J, Wisse M, Collins SH (2011) The effect of ankle foot orthosis stiffness on the energy cost of walking: a simulation study. *Clin biomech* 26(9):955–61. <https://doi.org/10.1016/j.clinbiomech.2011.05.007>

57. Kobayashi T, Leung AKL, Akazawa Y, Hutchins SW (2011) Design of a stiffness-adjustable ankle-foot orthosis and its effect on ankle joint kinematics in patients with stroke. *Gait Posture* 33(4):721–723. <https://doi.org/10.1016/j.gaitpost.2011.02.005>
58. Lee S, Sankai Y (2002) Power assist control for walking aid with HAL-3 based on EMG and impedance adjustment around knee joint. *IEEE/RSJ Int Conf Intell Robots Syst* 2(October):1499–1504. <https://doi.org/10.1109/IRDS.2002.1043967>
59. Delp SL, Anderson FC, Arnold AS, Loan P, John CT, Guendelman E (2007) OpenSim: Open-source software to create and analyze dynamic simulations of movement. *IEEE Trans Biomedical Eng* 54(11):1940–50
60. Seth A, Sherman M, Eastman P, Delp S (2010) Minimal formulation of joint motion for biomechanisms. *Nonlinear Dyn* 62:291–303
61. Sherman MA, Seth A, Delp SL (2011) Simbody: multibody dynamics for biomedical research. *Procedia IUTAM* 2:241–261
62. McGuan S (2001) From bubblemen to skeletons. *SAE Digital Human Modeling for Design and Engineering Conference*
63. Damsgaard M, Rasmussen J, Christensen ST, Surma E, de Zee M (2006) Analysis of musculoskeletal systems in the anybody modeling system. *Simul Model Pract Theory* 14(8):1100–1111
64. Visual3d biomechanics research software. <https://c-motion.com/products/visual3d>. Accessed 12 Mar 2020
65. D-Flow, Motekforce Link. <https://www.motekmedical.com/software/d-flow/>. Accessed 12 Mar 2020
66. Van den Bogert AJ, Geijtenbeek T, Even-Zohar O, Steenbrink F, Hardin EC (2013) A real-time system for biomechanical analysis of human movement and muscle function. *Med Biol Eng Comput* 51(10):1069–1077
67. Coppelia Robotics V-REP: Create. Compose. Simulate. Any Robot. <http://www.coppeliarobotics.com>. 2016. Accessed on 31 July 2014
68. Kulić D, Venture G, Yamane K, Demircan E, Mizuuchi I, Mombaur K (2016) Anthropomorphic movement analysis and synthesis: a survey of methods and applications. *IEEE Trans Robot* 32(4):776–795
69. Demircan E, Recinos E, Abella JR, Khoo I, Teng S, Wu W (2019) Perception accuracy of vibrotactile feedback during locomotion. In: c16th International Conference on Ubiquitous Robots, UR 2019, Jeju, South Korea, June 24–27, 2019, pp. 673–677. <https://doi.org/10.1109/URAI.2019.8768771>
70. Unity Asset Store. <https://assetstore.unity.com/>. Accessed 12 Mar 2020
71. Demircan E (2012) Robotics-based reconstruction and synthesis of human motion. PhD Thesis, Stanford University, Stanford
72. Math.NET Symbolics. <https://symbolics.mathdotnet.com/>. Accessed 12 Mar 2020
73. C++ Mathematical expression library (ExprTk). <https://github.com/ArashPartow/exprtk>. Accessed 12 Mar 2020
74. C++/C# Numerical analysis library. <https://www.alglib.net/>. Accessed 12 Mar 2020
75. Mladenova C, Mladenov I (2011) Vector decomposition of finite rotations. *Rep Math Phys* 68(1):107–17
76. Brezov D, Mladenova C, Mladenov I (2012) Vector decomposition of rotations. *Geom Sym Phys* 28:67–103
77. Dobrowolski P (2015) Swing-twist decomposition in clifford algebra. *CoRR*
78. Oculus developer center. <https://developer.oculus.com/>. Accessed 12 Mar 2020
79. Perception neuron. <https://neuronmocap.com/>. Accessed 12 Mar 2020
80. Khatib O, Demircan E, DeSapio V, Sentis L, Besier T, Delp S (2009) Robotics-based synthesis of human motion. *J Physiol* 103:211–219
81. Abella J, Demircan E (2019) A multi-body simulation framework for live motion tracking and analysis within the unity environment, pp. 654–659. <https://doi.org/10.1109/URAI.2019.8768659>
82. Rogers JA (2013) A clear advance in soft actuators. *Science* 341:968–969
83. Majidi C (2014) Soft robotics: a perspective—current trends and prospects for the future. *Soft Robot* 1:5–11
84. Yeo W-H, Kim Y-S, Lee J, Ameen A, Shi L, Li M (2013) Multifunctional epidermal electronics printed directly onto the skin. *Adv Mater* 25:2773–2778
85. Shull T, Lurie K, Shin M, Besier T, Cutkosky M (2010) Haptic gait retraining for treating and preventing knee osteoarthritis. *World Haptics, Washington*
86. Willson JD, Sharpee R, Meardon SA, Kernozek TW (2014) Effects of step length on patellofemoral joint stress in female runners with and without patellofemoral pain. *Clin Biomech* 29(3):243–247
87. Heiderscheit BC, Chumanov ES, Michalski MP, Wille CM, Ryan MB (2011) Effects of step rate manipulation on joint mechanics during running. *Med Sci Sports Exerc* 43(2):296–302
88. Bonacci J, Vicenzino B, Spratford W, Collins P (2014) Take your shoes off to reduce patellofemoral joint stress during running. *Br J Sports Med* 48(6):425–428
89. Lieberman DE, Venkadesan M, Werbel WA, Daoud AI, D'Andrea S, Davis IS, Mang'Eni RO, Pitsiladis Y (2010) Foot strike patterns and collision forces in habitually barefoot versus shod runners. *Nature* 463(7280):531–535
90. Sigrist R, Rauter G, Riener R, Wolf P (2012) Augmented visual, auditory, haptic, and multimodal feedback in motor learning: a review. *Psychon Bull Rev* 20:21–53
91. <https://www.statista.com/statistics/227423/number-of-joggers-and-runners-usa/>. Accessed 12 Mar 2020, S
92. <https://runningusa.org/>. Accessed 12 Mar 2020, U.S.R.T.R
93. Kalak N, Gerber M, Kirov R, Mikoteit T, Yordanova J, Pühse U, Holsboer-Trachslar E, Brand S (2012) Daily morning running for 3 weeks improved sleep and psychological functioning in healthy adolescents compared with controls. *J Adolesc Health* 51(6):615–622

Publisher's Note

Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Submit your manuscript to a SpringerOpen[®] journal and benefit from:

- Convenient online submission
- Rigorous peer review
- Open access: articles freely available online
- High visibility within the field
- Retaining the copyright to your article

Submit your next manuscript at ► [springeropen.com](https://www.springeropen.com)